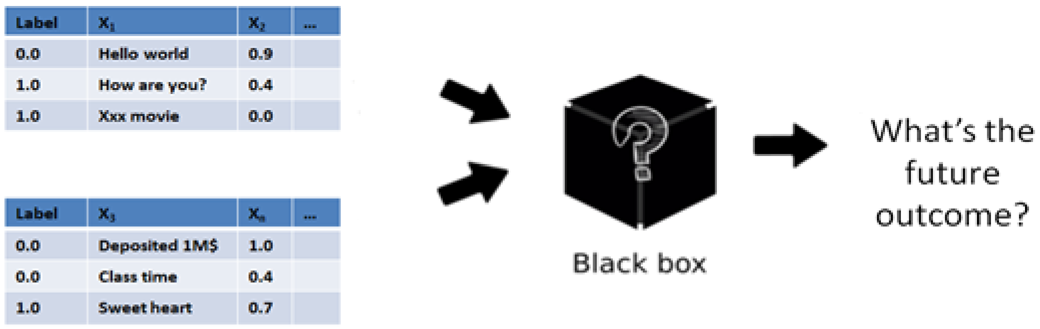
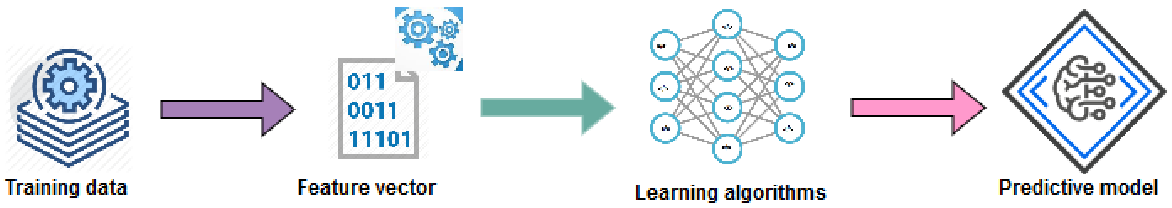
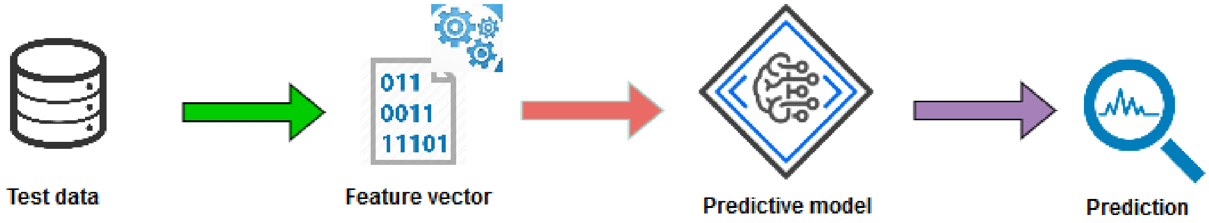
Chapter 01: Basic Python and Linear Algebra for Predictive Analytics

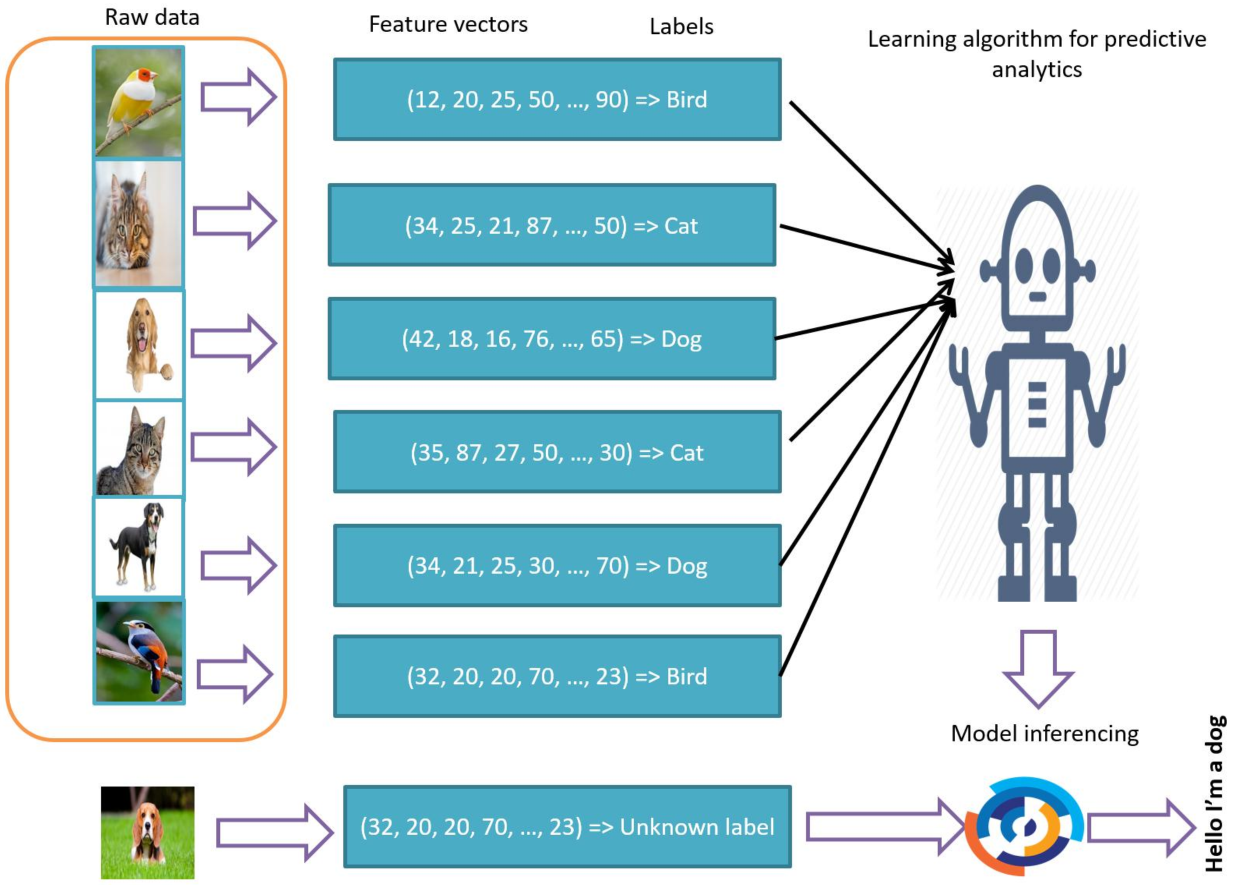


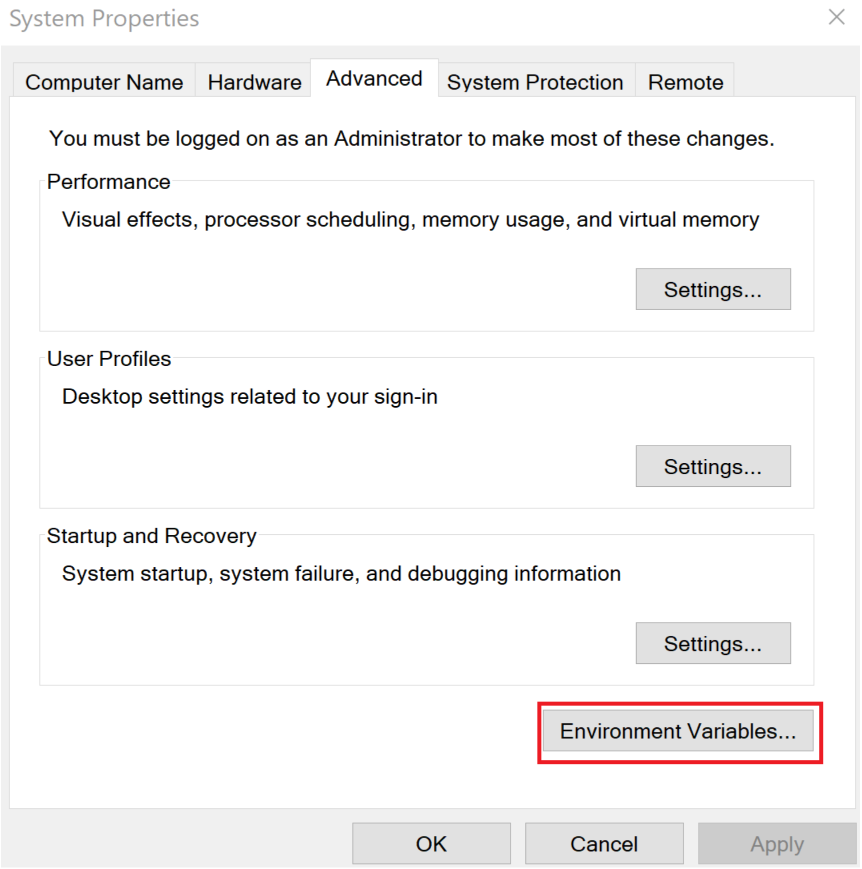
Label	X_1	X_2	...
0.0	Hello world	0.9	
1.0	How are you?	0.4	
1.0	Xxx movie	0.0	

Label	X_3	X_n	...
0.0	Deposited 1M$	1.0	
0.0	Class time	0.4	
1.0	Sweet heart	0.7	






Raw data
Feature vectors
Labels
Learning algorithm for predictive analytics
(12, 20, 25, 50, ..., 90) => Bird
(34, 25, 21, 87, ..., 50) => Cat
(42, 18, 16, 76, ..., 65) => Dog
(35, 87, 27, 50, ..., 30) => Cat
(34, 21, 25, 30, ..., 70) => Dog
(32, 20, 20, 70, ..., 23) => Bird
Model inferencing
(32, 20, 20, 70, ..., 23) => Unknown label
Hello I'm a dog

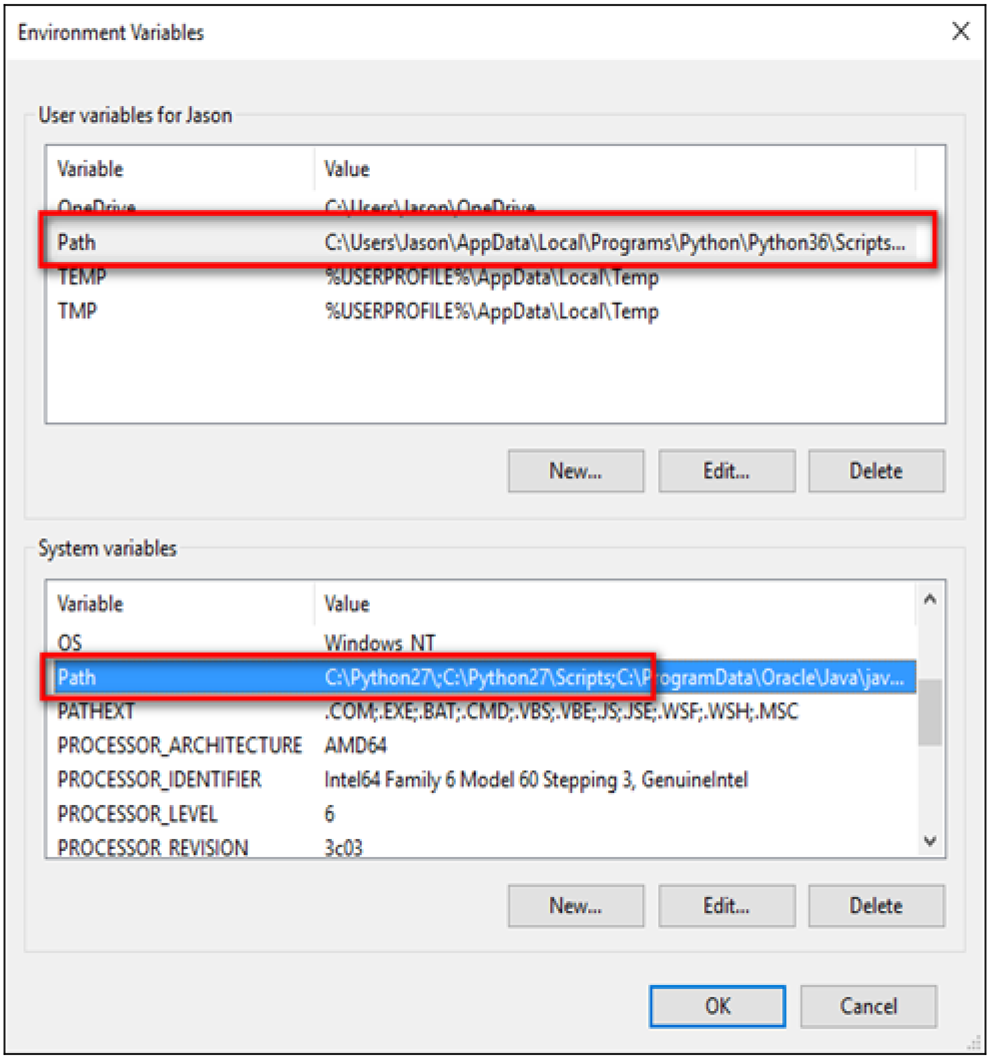


You must be logged on as an Administrator to make most of these changes.

Visual effects, processor scheduling, memory usage, and virtual memory

Desktop settings related to your sign-in

System startup, system failure, and debugging information



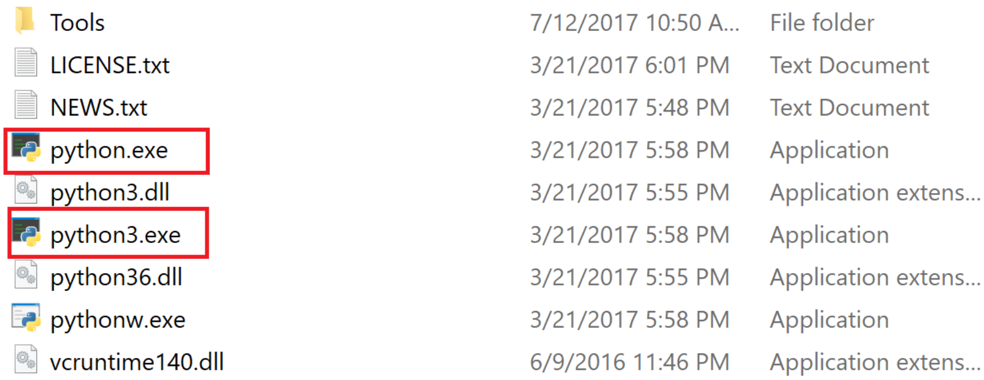
Environment Variables

User variables for Jason

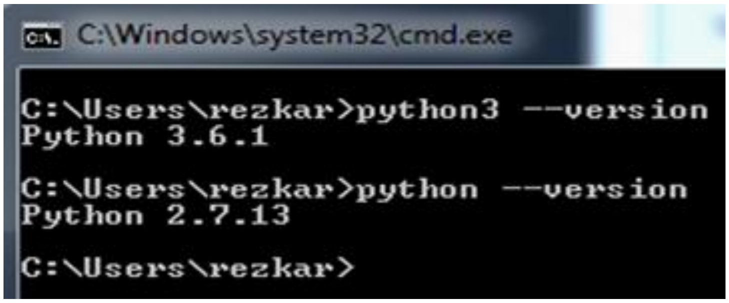
Variable	Value
OneDrive	C:\Users\Jason\OneDrive
Path	C:\Users\Jason\AppData\Local\Programs\Python\Python36\Scripts...
TEMP	%USERPROFILE%\AppData\Local\Temp
TMP	%USERPROFILE%\AppData\Local\Temp

System variables

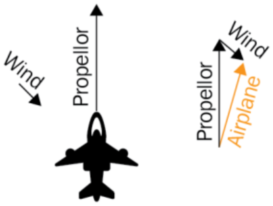
Variable	Value
OS	Windows_NT
Path	C:\Python27\;C:\Python27\Scripts;C:\ProgramData\Oracle\Java\jav...
PATHEXT	.COM;.EXE;.BAT;.CMD;.VBS;.VBE;.JS;.JSE;.WSF;.WSH;.MSC
PROCESSOR_ARCHITECTURE	AMD64
PROCESSOR_IDENTIFIER	Intel64 Family 6 Model 60 Stepping 3, GenuineIntel
PROCESSOR_LEVEL	6
PROCESSOR_REVISION	3c03

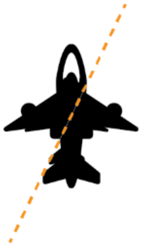


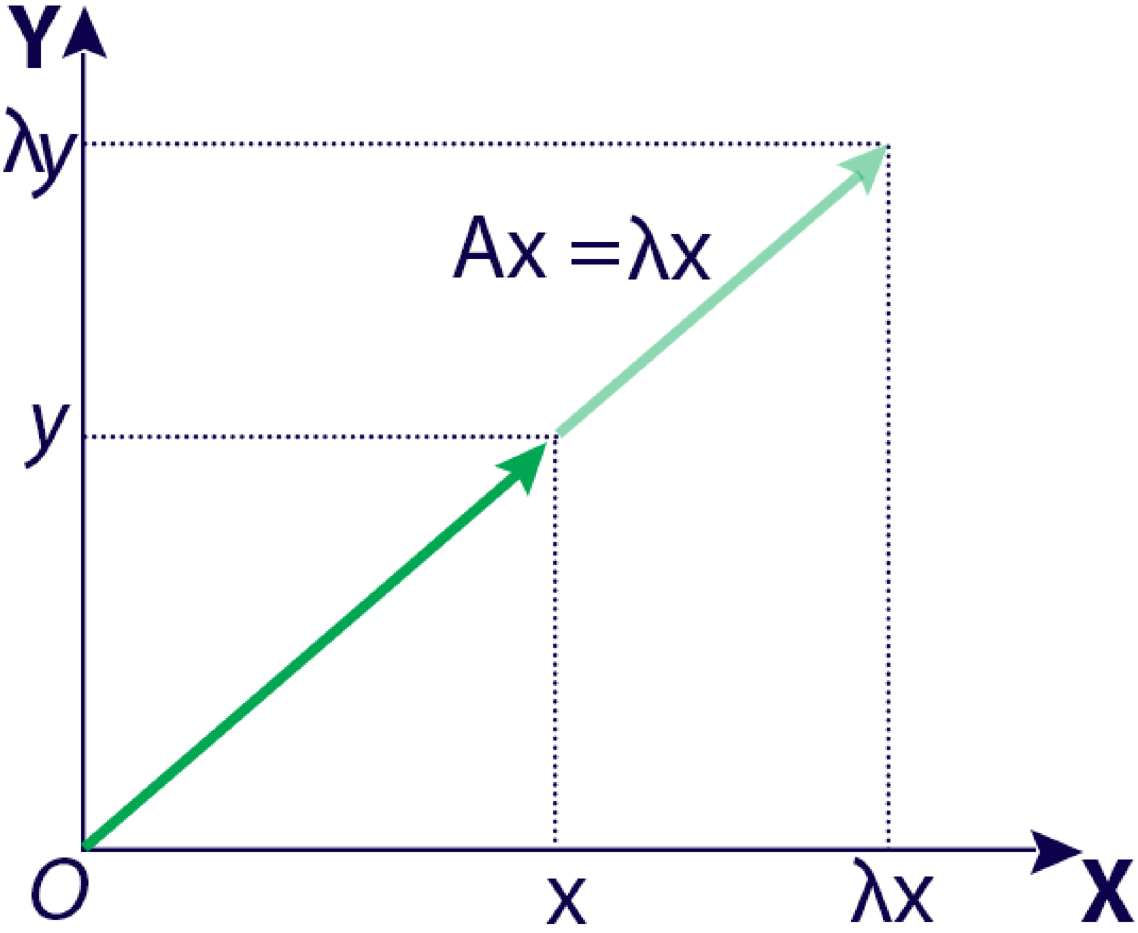
Tools	7/12/2017 10:50 A...	File folder
LICENSE.txt	3/21/2017 6:01 PM	Text Document
NEWS.txt	3/21/2017 5:48 PM	Text Document
python.exe	3/21/2017 5:58 PM	Application
python3.dll	3/21/2017 5:55 PM	Application extens...
python3.exe	3/21/2017 5:58 PM	Application
python36.dll	3/21/2017 5:55 PM	Application extens...
pythonw.exe	3/21/2017 5:58 PM	Application
vcruntime140.dll	6/9/2016 11:46 PM	Application extens...

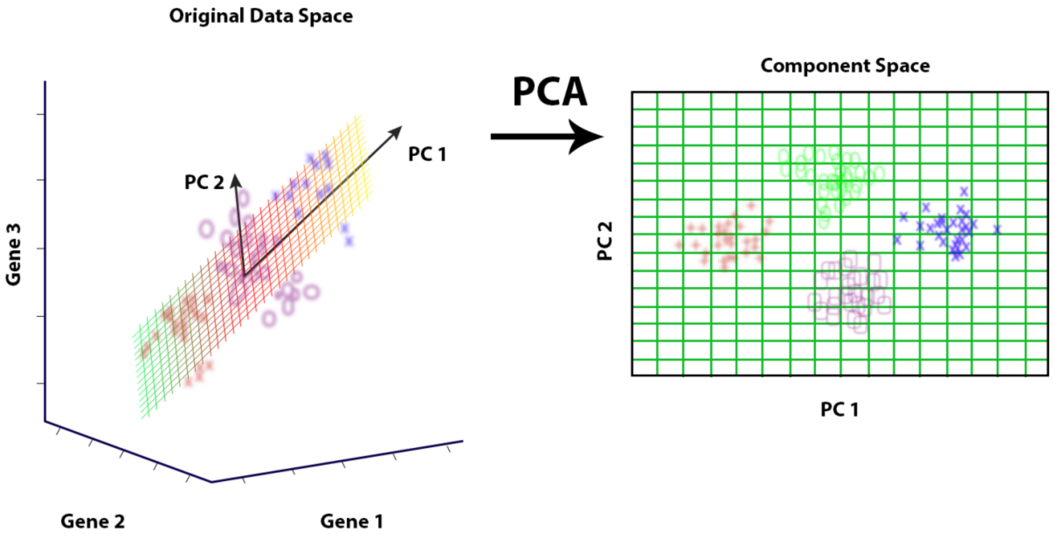


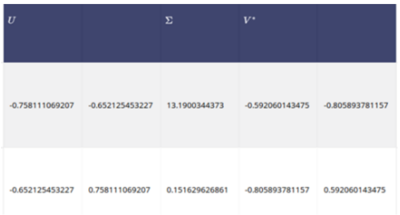
```
C:\Users\rezkar>python3 --version
Python 3.6.1

C:\Users\rezkar>python --version
Python 2.7.13

C:\Users\rezkar>
```





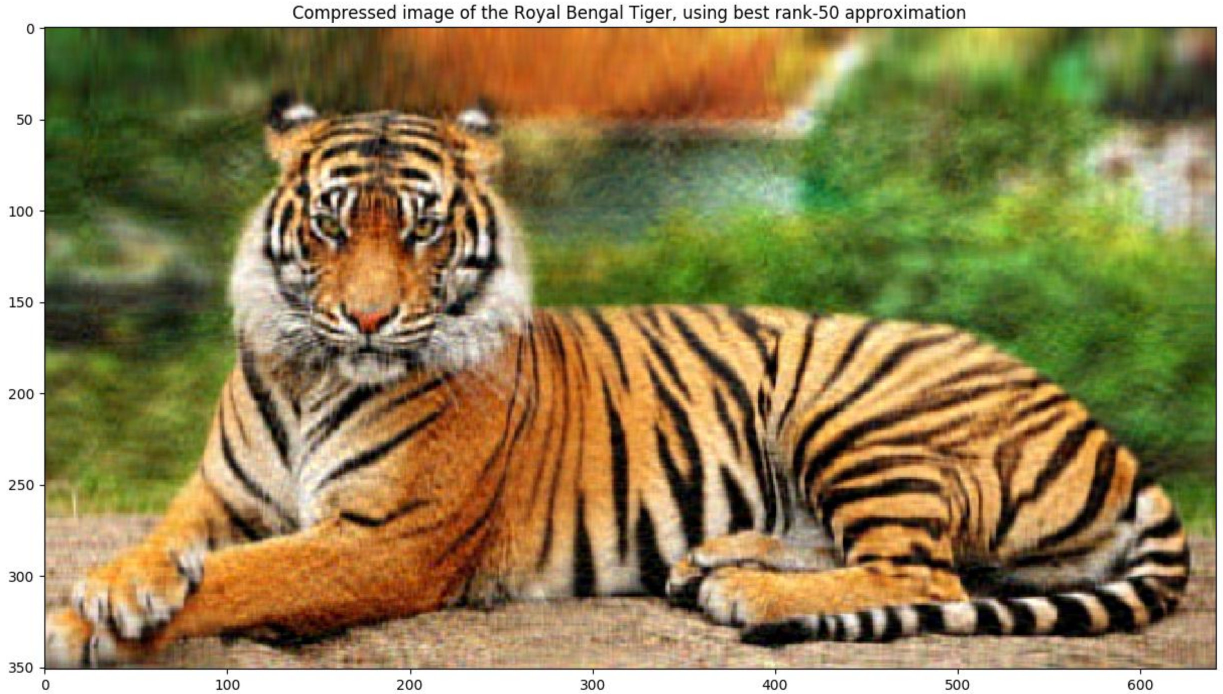

Y
λy
Ax = λx
y
O
x
λx
X

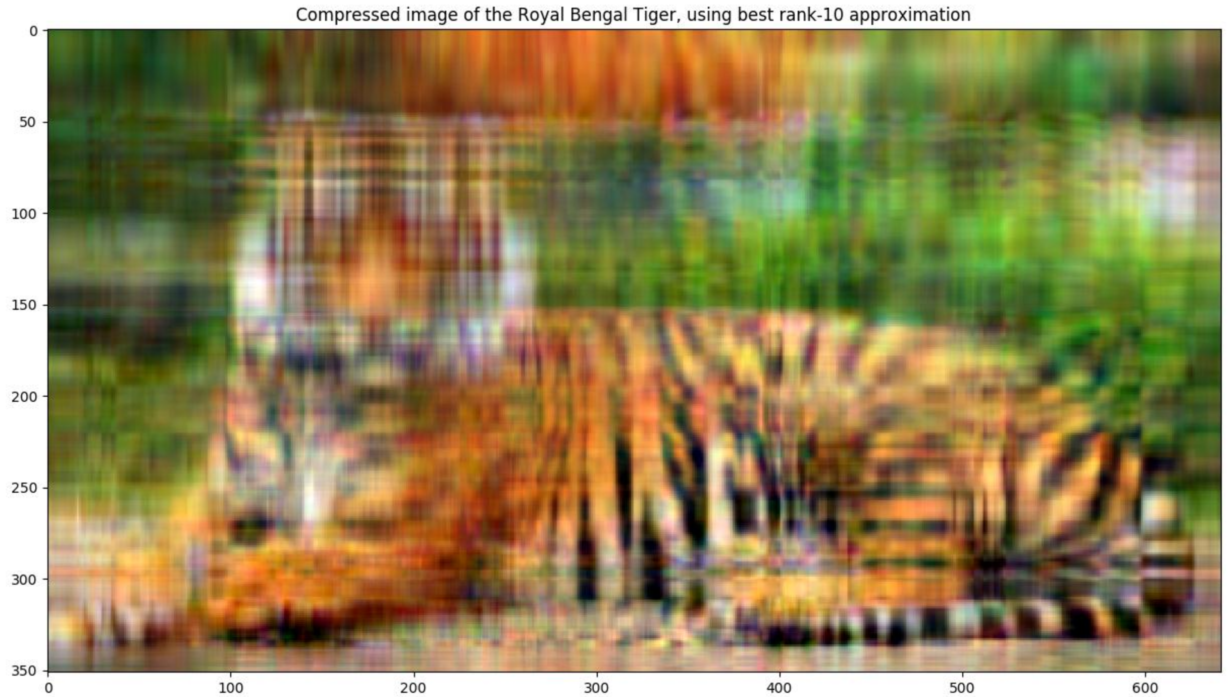


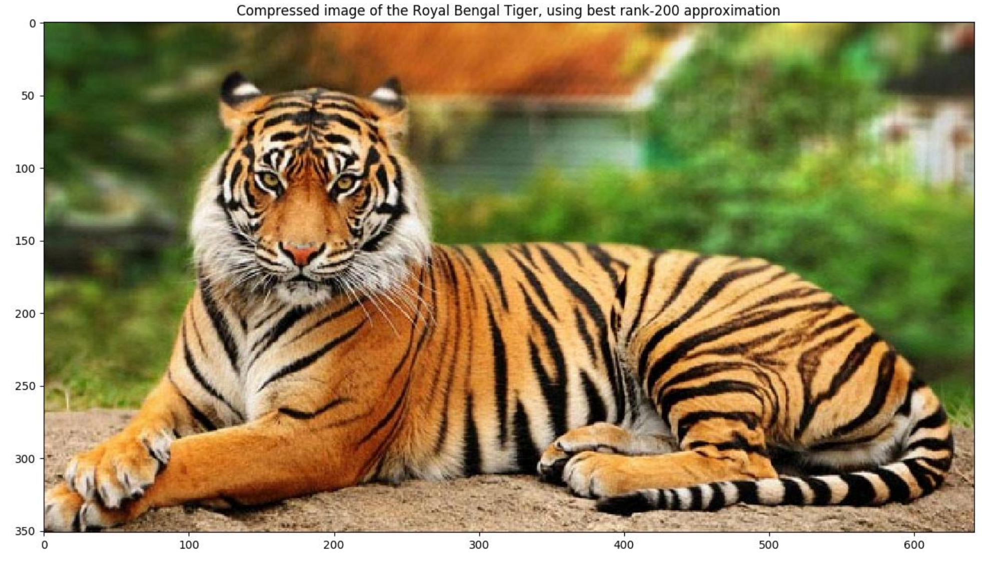


U		Σ	V^*	
-0.758111069207	-0.652125453227	13.1900344373	-0.592060143475	-0.805893781157
-0.652125453227	0.758111069207	0.151629626861	-0.805893781157	0.592060143475

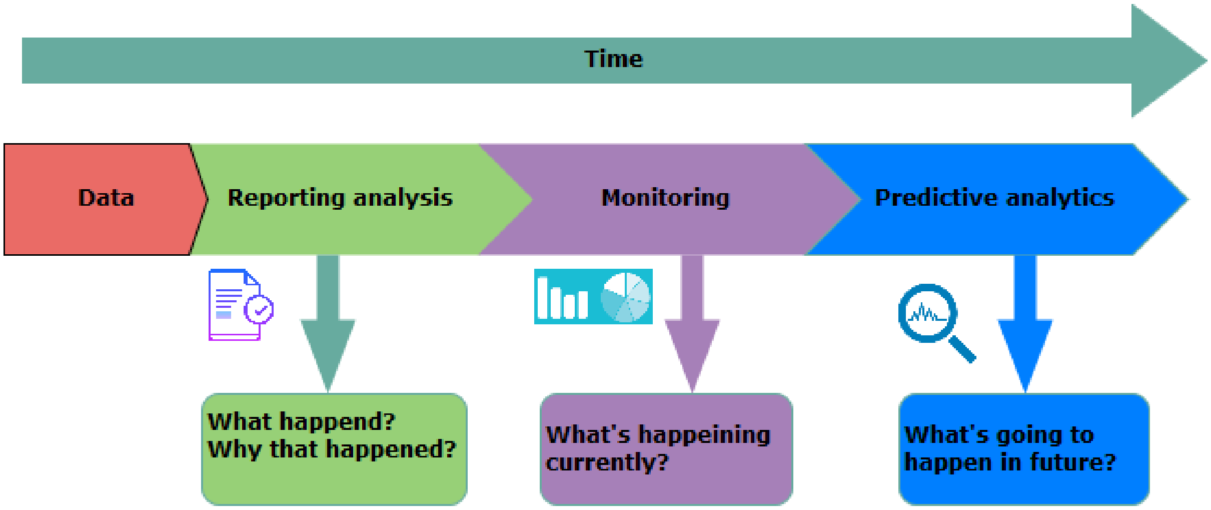
Royal Bengal Tiger, Sundarban, Bangladesh
0
50
100
150
200
250
300
350
0
100
200
300
400
500
600

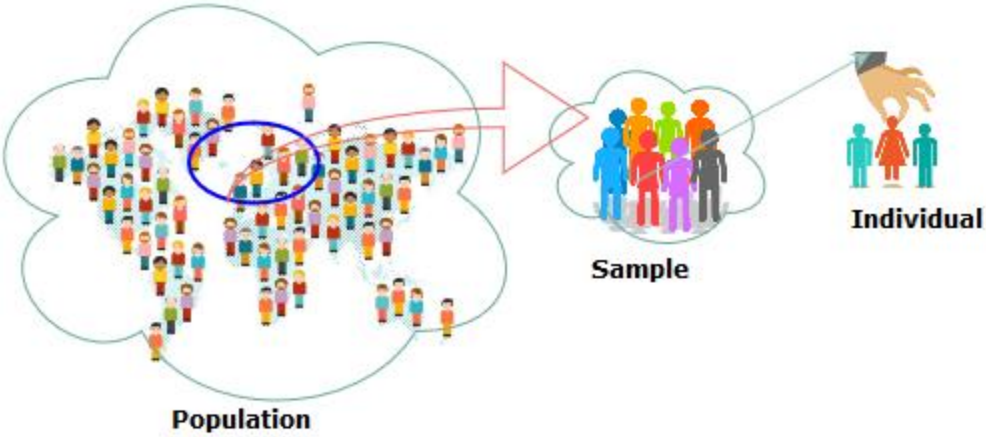

Compressed image of the Royal Bengal Tiger, using best rank-50 approximation

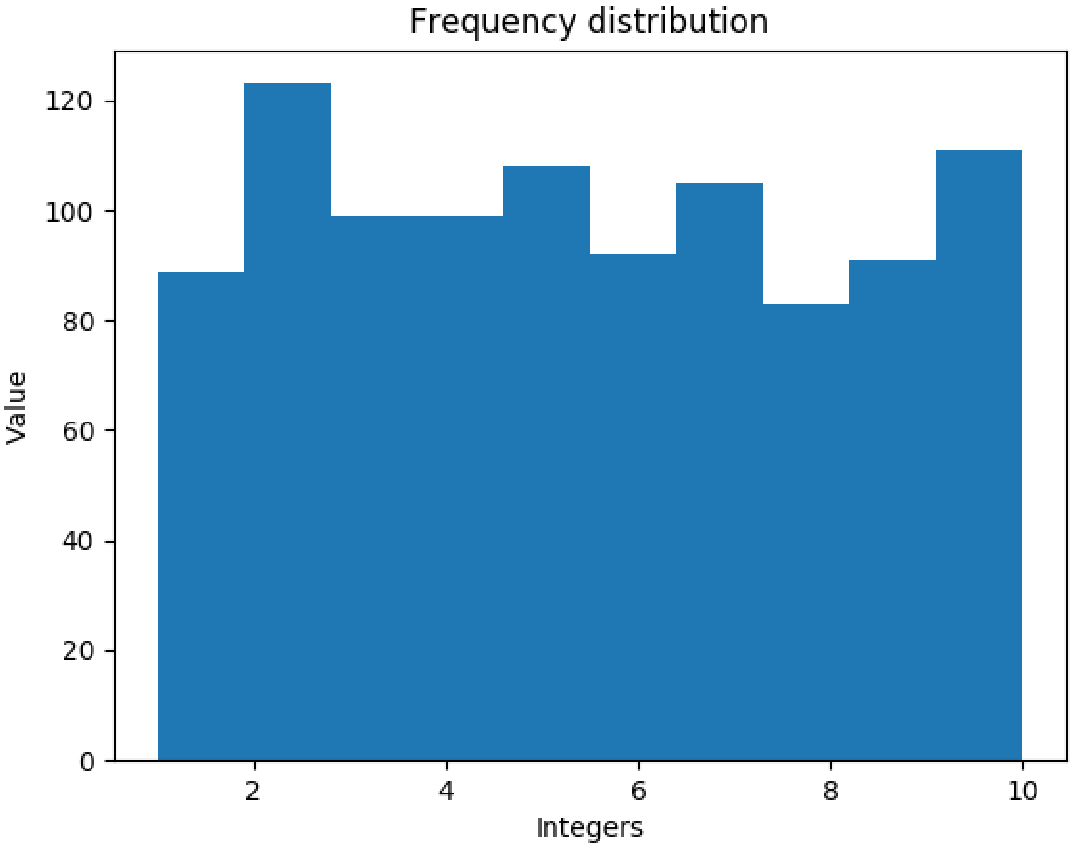

Compressed image of the Royal Bengal Tiger, using best rank-10 approximation
0
50
100
150
200
250
300
350
0
100
200
300
400
500
600

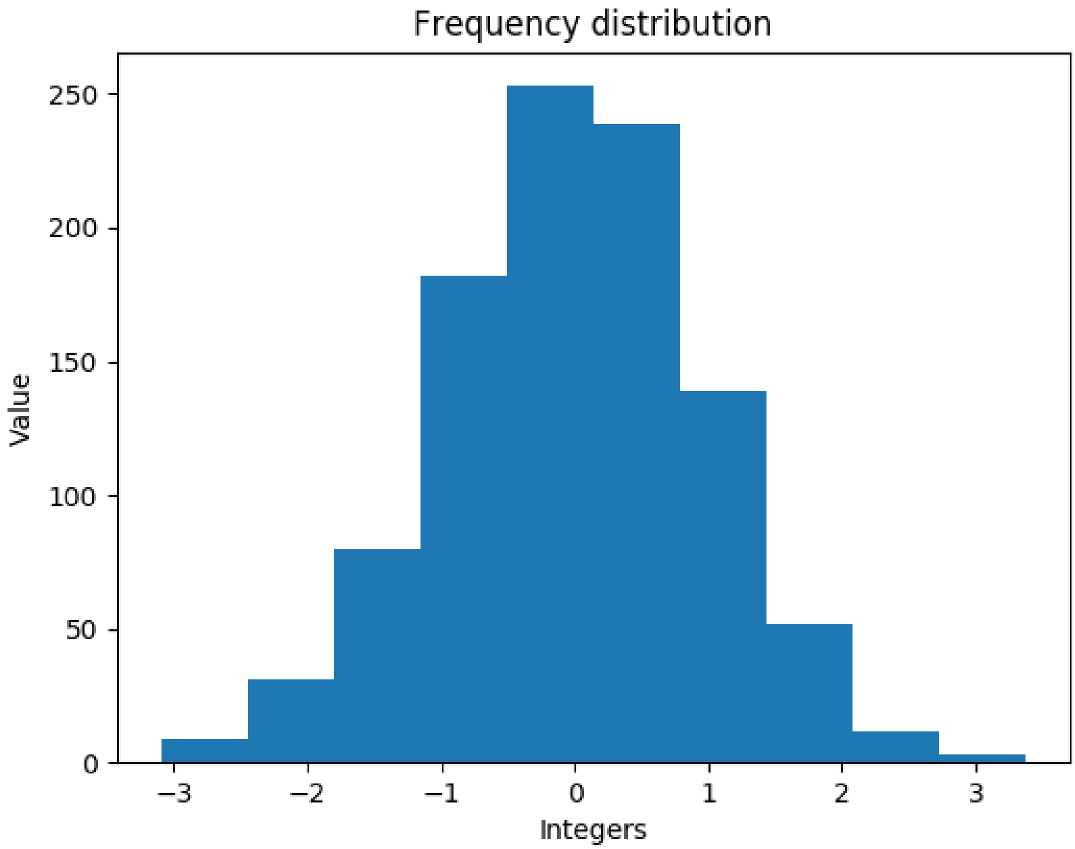

Compressed image of the Royal Bengal Tiger, using best rank-200 approximation
0
50
100
150
200
250
300
350
0
100
200
300
400
500
600

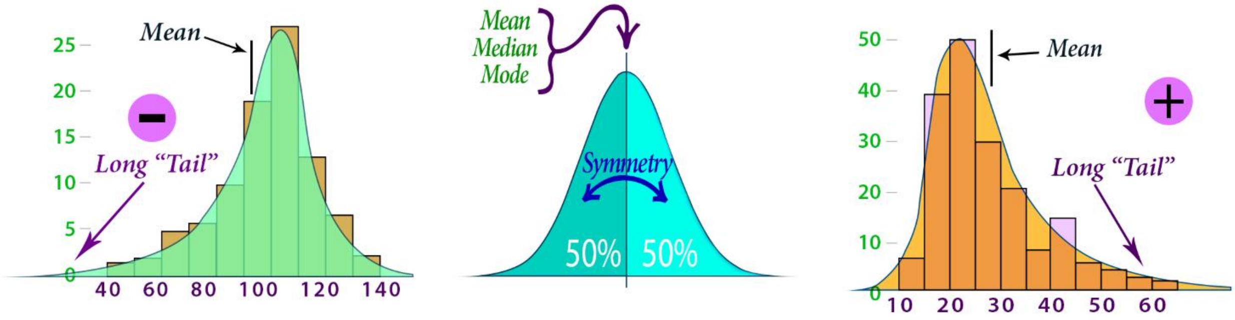
Chapter 02: Statistics, Probability, and Information Theory for Predictive Modeling

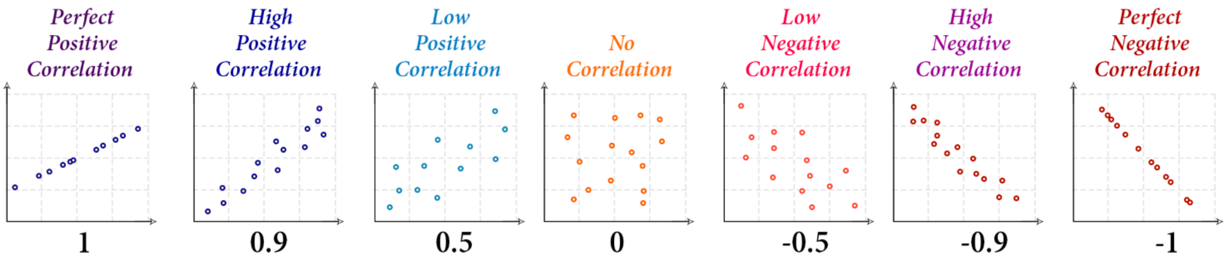


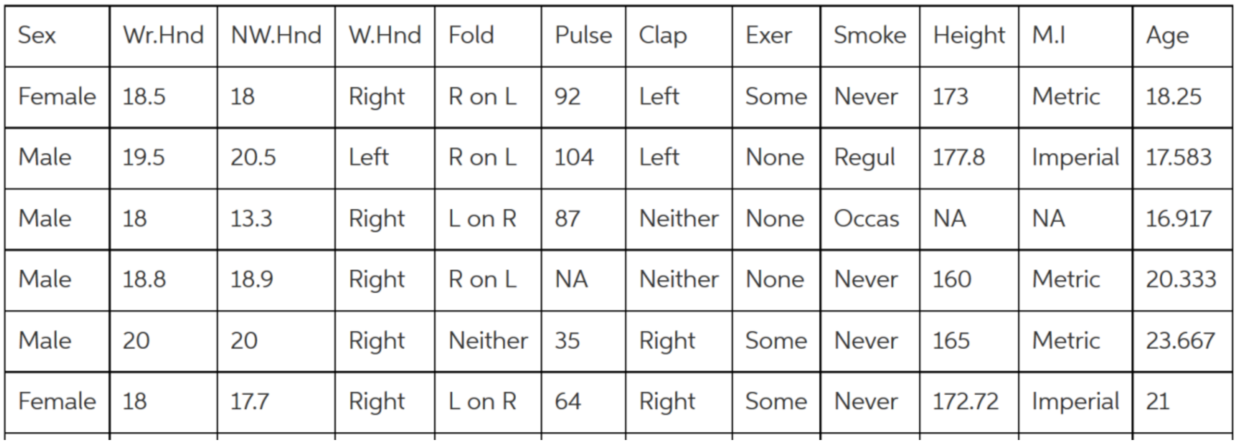



Frequency distribution
Value
0
20
40
60
80
100
120
2
4
6
8
10
Integers

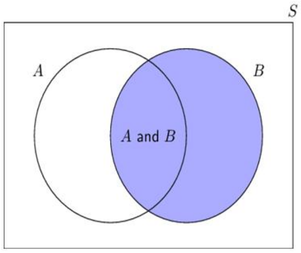

Frequency distribution
Value
250
200
150
100
50
0
−3
−2
−1
0
1
2
3
Integers

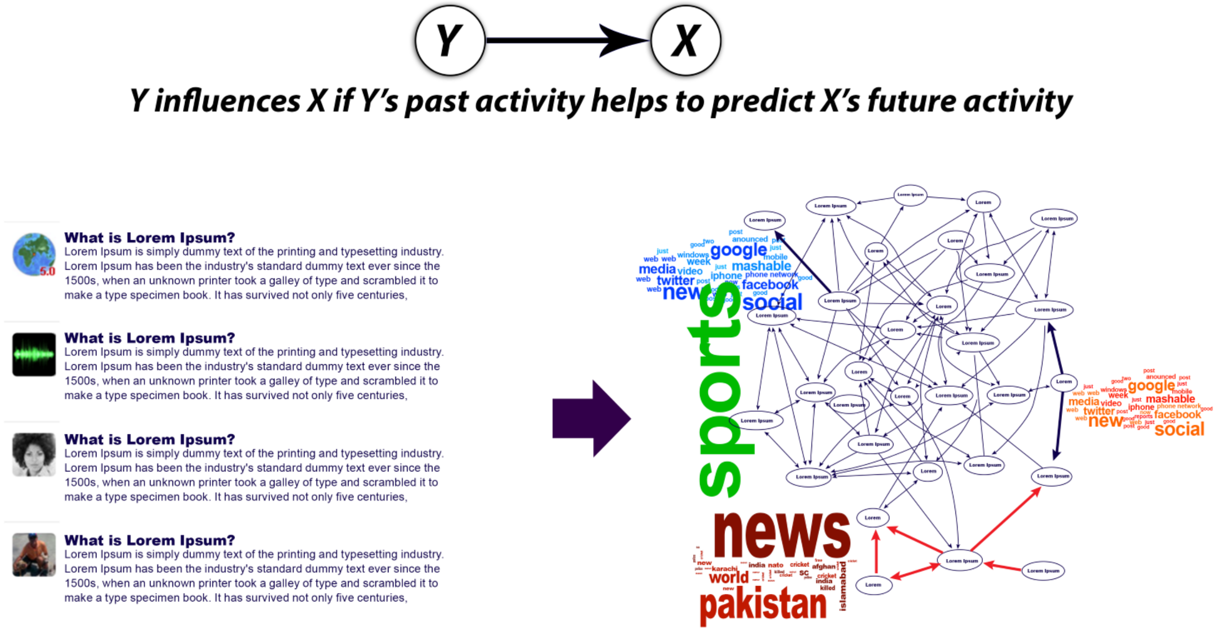

Mean
25
20
15
10
5
0
Long "Tail"
40
60
80
100
120
140
Mean
Median
Mode
Symmetry
50%
50%
50
40
30
20
10
0
Mean
Long "Tail"
10
20
30
40
50
60





Sex	Wr.Hnd	NW.Hnd	W.Hnd	Fold	Pulse	Clap	Exer	Smoke	Height	M.I	Age
Female	18.5	18	Right	R on L	92	Left	Some	Never	173	Metric	18.25
Male	19.5	20.5	Left	R on L	104	Left	None	Regul	177.8	Imperial	17.583
Male	18	13.3	Right	L on R	87	Neither	None	Occas	NA	NA	16.917
Male	18.8	18.9	Right	R on L	NA	Neither	None	Never	160	Metric	20.333
Male	20	20	Right	Neither	35	Right	Some	Never	165	Metric	23.667
Female	18	17.7	Right	L on R	64	Right	Some	Never	172.72	Imperial	21





Y influences X if Y's past activity helps to predict X's future activity

What is Lorem Ipsum?
Lorem Ipsum is simply dummy text of the printing and typesetting industry. Lorem Ipsum has been the industry's standard dummy text ever since the 1500s, when an unknown printer took a galley of type and scrambled it to make a type specimen book. It has survived not only five centuries,

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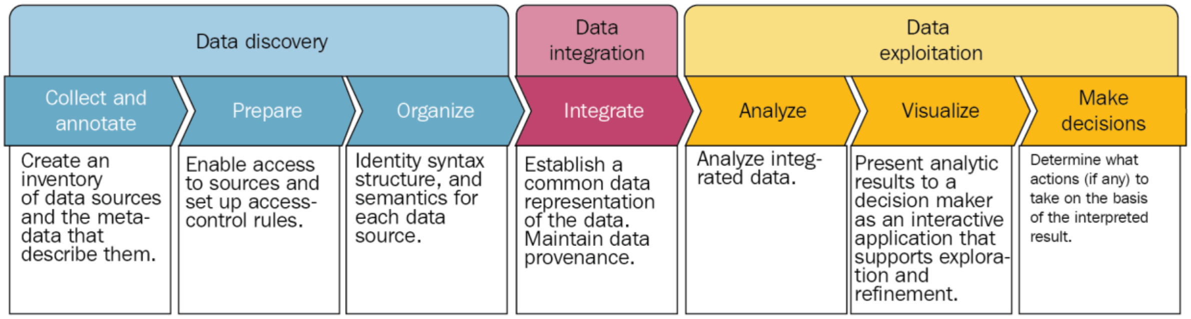
Chapter 03: From Data to Decisions – Getting Started with TensorFlow



Create an inventory of data sources and the meta-data that describe them.

Enable access to sources and set up access-control rules.

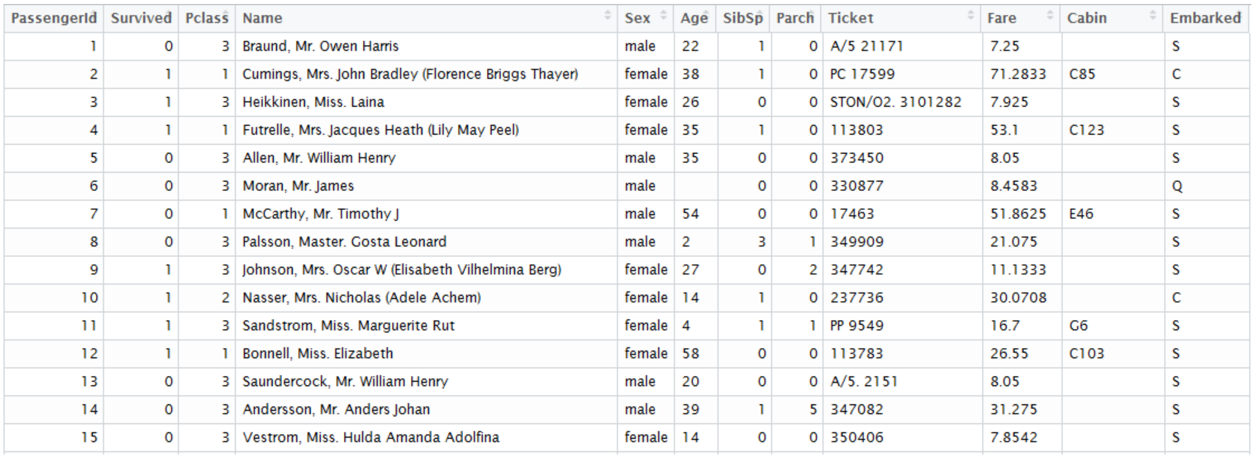
Identity syntax structure, and semantics for each data source.

Establish a common data representation of the data. Maintain data provenance.

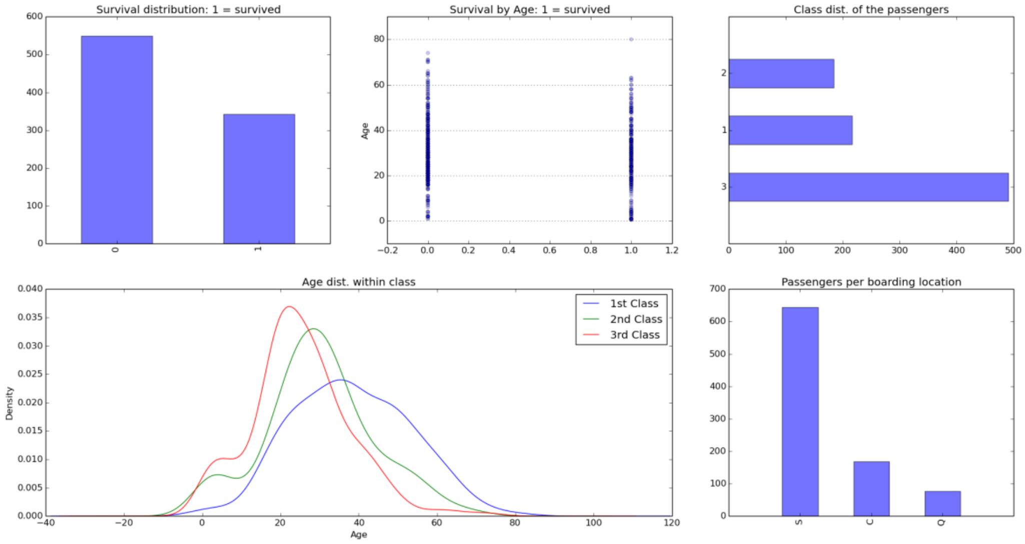
Analyze integrated data.

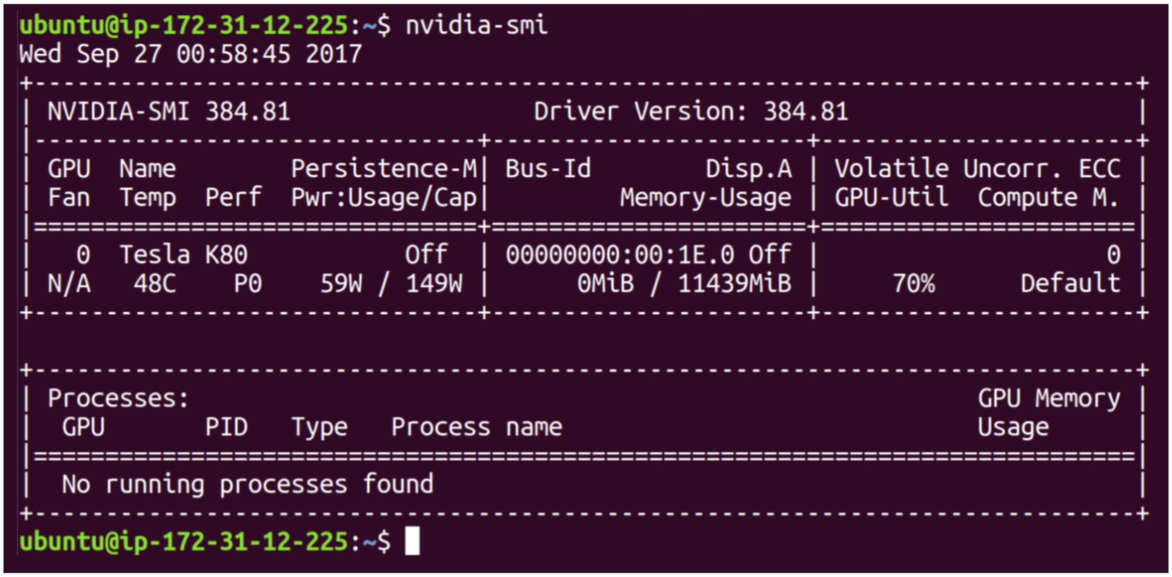
Present analytic results to a decision maker as an interactive application that supports exploration and refinement.

Determine what actions (if any) to take on the basis of the interpreted result.

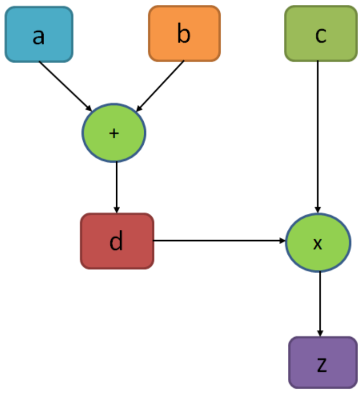


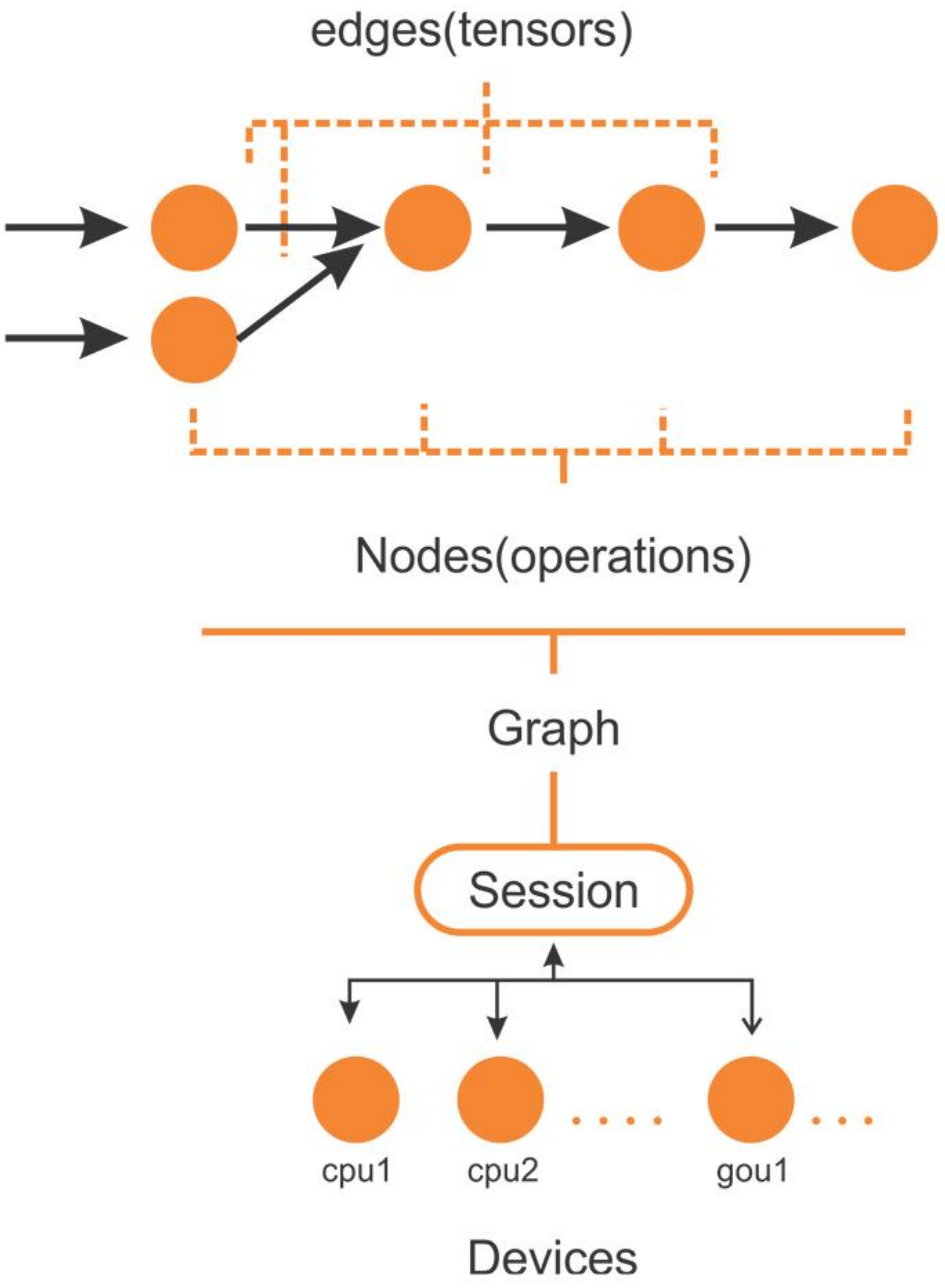
PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
1	0	3	Braund, Mr. Owen Harris	male	22	1	0	A/5 21171	7.25		S
2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Thayer)	female	38	1	0	PC 17599	71.2833	C85	C
3	1	3	Heikkinen, Miss. Laina	female	26	0	0	STON/O2. 3101282	7.925		S
4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35	1	0	113803	53.1	C123	S
5	0	3	Allen, Mr. William Henry	male	35	0	0	373450	8.05		S
6	0	3	Moran, Mr. James	male		0	0	330877	8.4583		Q
7	0	1	McCarthy, Mr. Timothy J	male	54	0	0	17463	51.8625	E46	S
8	0	3	Palsson, Master. Gosta Leonard	male	2	3	1	349909	21.075		S
9	1	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27	0	2	347742	11.1333		S
10	1	2	Nasser, Mrs. Nicholas (Adele Achem)	female	14	1	0	237736	30.0708		C
11	1	3	Sandstrom, Miss. Marguerite Rut	female	4	1	1	PP 9549	16.7	G6	S
12	1	1	Bonnell, Miss. Elizabeth	female	58	0	0	113783	26.55	C103	S
13	0	3	Saundercock, Mr. William Henry	male	20	0	0	A/5. 2151	8.05		S
14	0	3	Andersson, Mr. Anders Johan	male	39	1	5	347082	31.275		S
15	0	3	Vestrom, Miss. Hulda Amanda Adolfina	female	14	0	0	350406	7.8542		S

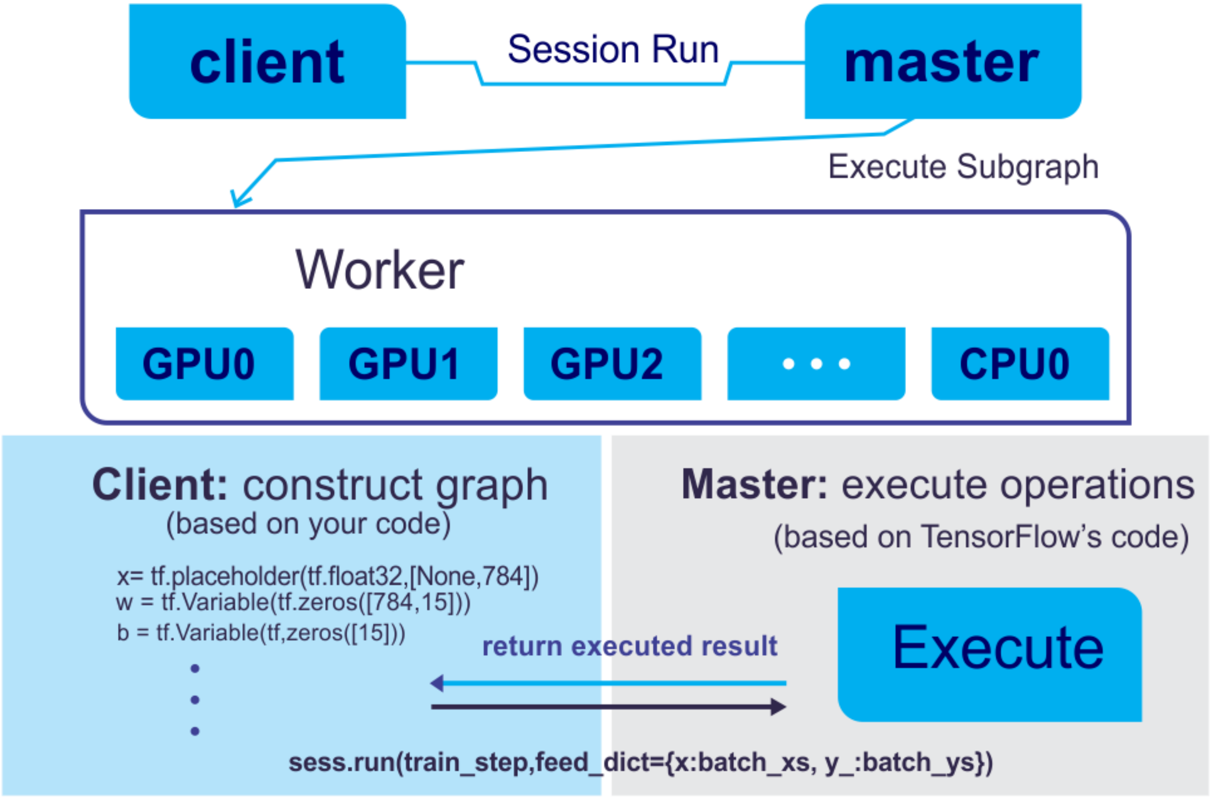




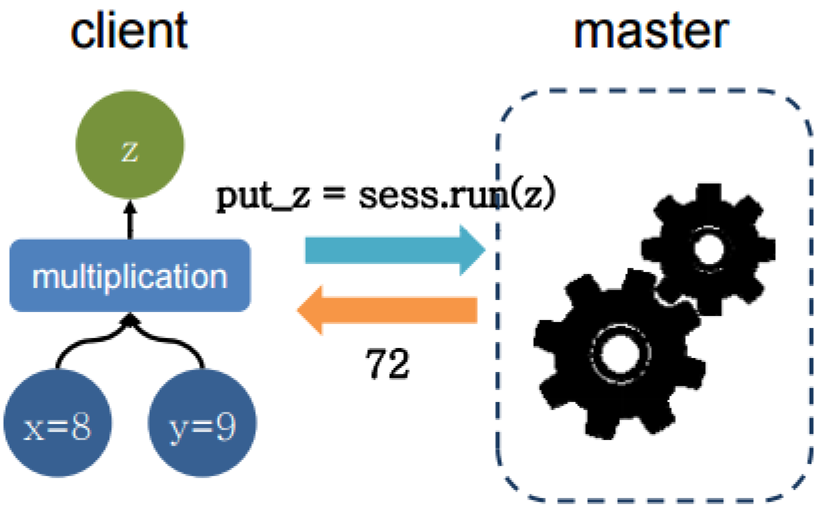
```
ubuntu@ip-172-31-12-225:~$ nvidia-smi
Wed Sep 27 00:58:45 2017
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 384.81                 Driver Version: 384.81                    |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|===============================+======================+======================|
|   0  Tesla K80           Off  | 00000000:00:1E.0 Off |                    0 |
| N/A   48C    P0    59W / 149W |      0MiB / 11439MiB |     70%      Default |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                       GPU Memory |
|  GPU       PID   Type   Process name                             Usage      |
|=============================================================================|
|  No running processes found                                                 |
+-----------------------------------------------------------------------------+
ubuntu@ip-172-31-12-225:~$ 
```


a
b
c
+
d
x
z

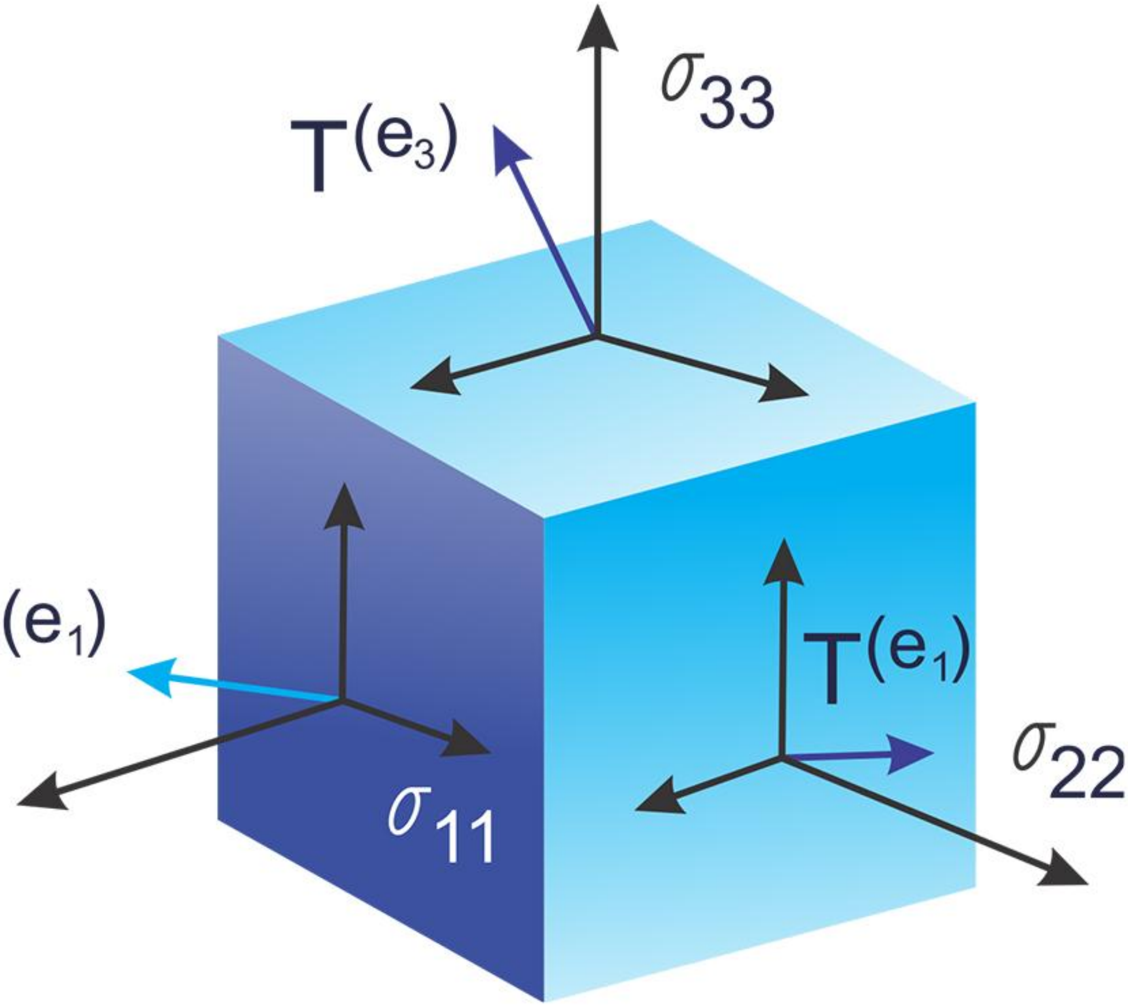

edges(tensors)
Nodes(operations)
Graph
Session
cpu1
cpu2
gou1
Devices

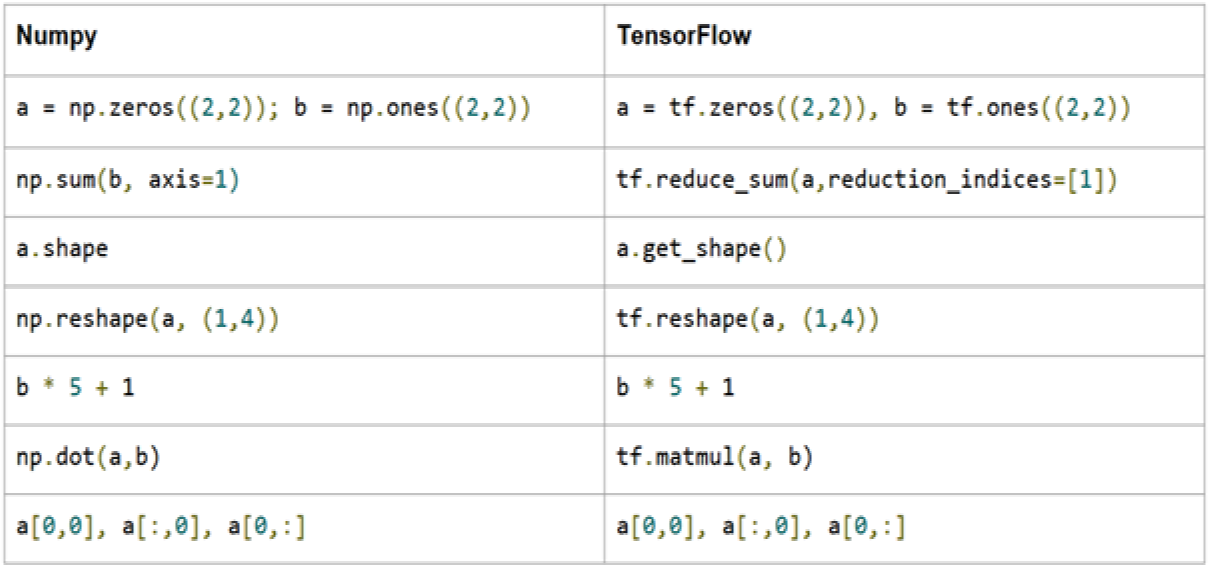


```
x= tf.placeholder(tf.float32,[None,784])
w = tf.Variable(tf.zeros([784,15]))
b = tf.Variable(tf,zeros([15]))
•
•
•
sess.run(train_step,feed_dict={x:batch_xs, y_:batch_ys})
```

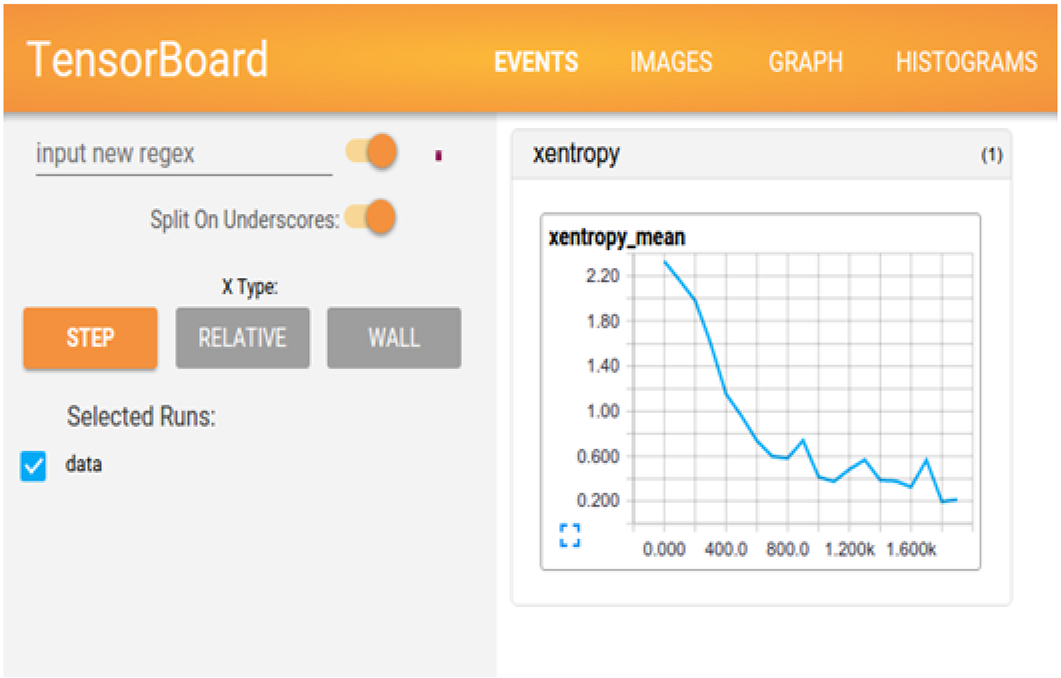


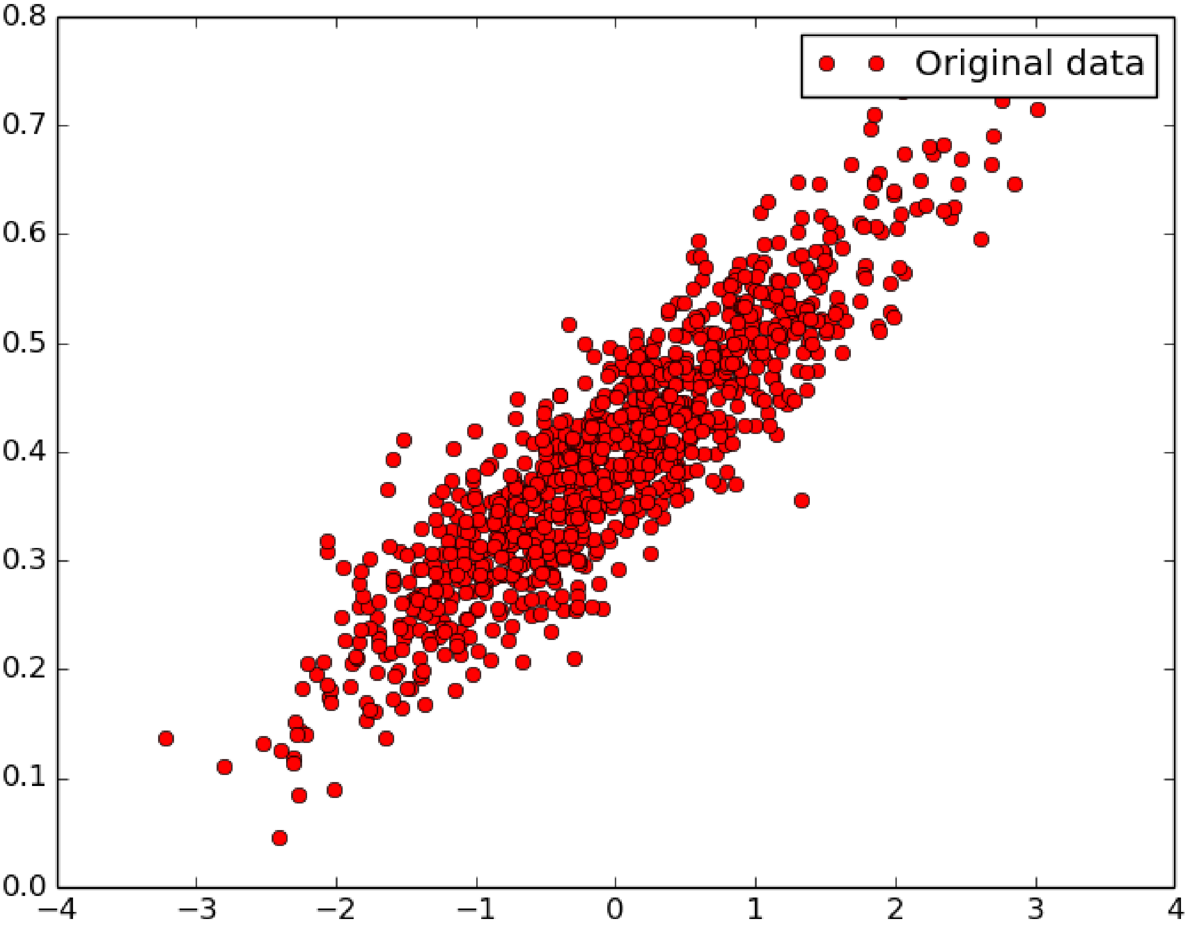
```
put_z = sess.run(z)
```

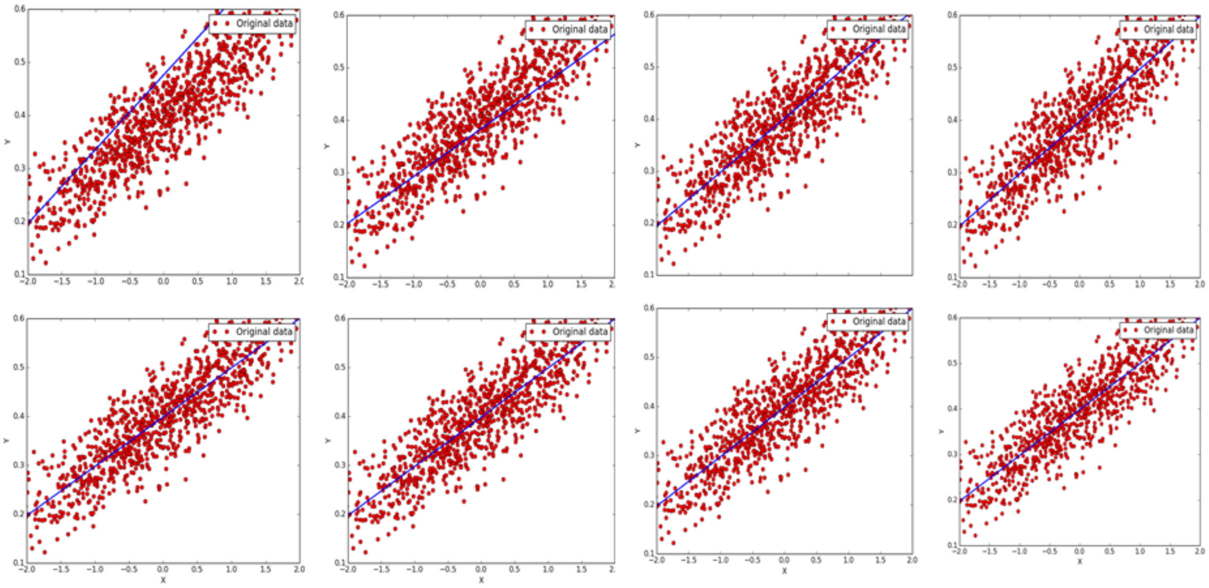

σ_{33}
$T^{(e_3)}$
$T^{(e_1)}$
$T^{(e_1)}$
σ_{22}
σ_{11}

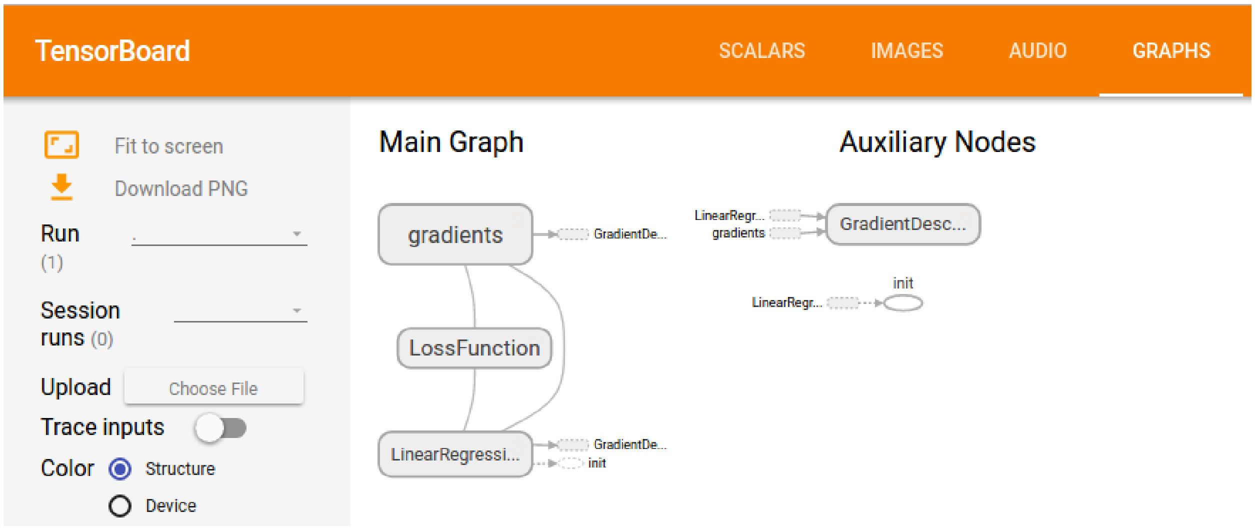


Numpy	TensorFlow
`a = np.zeros((2,2)); b = np.ones((2,2))`	`a = tf.zeros((2,2)), b = tf.ones((2,2))`
`np.sum(b, axis=1)`	`tf.reduce_sum(a,reduction_indices=[1])`
`a.shape`	`a.get_shape()`
`np.reshape(a, (1,4))`	`tf.reshape(a, (1,4))`
`b * 5 + 1`	`b * 5 + 1`
`np.dot(a,b)`	`tf.matmul(a, b)`
`a[0,0], a[:,0], a[0,:]`	`a[0,0], a[:,0], a[0,:]`

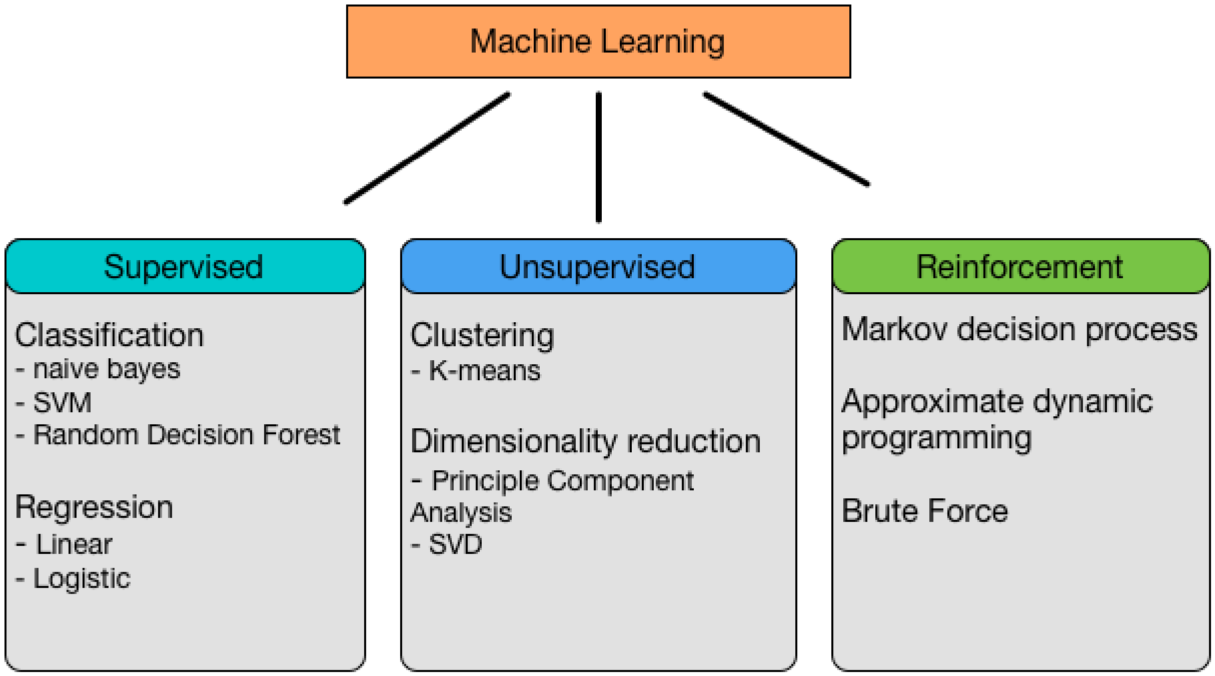


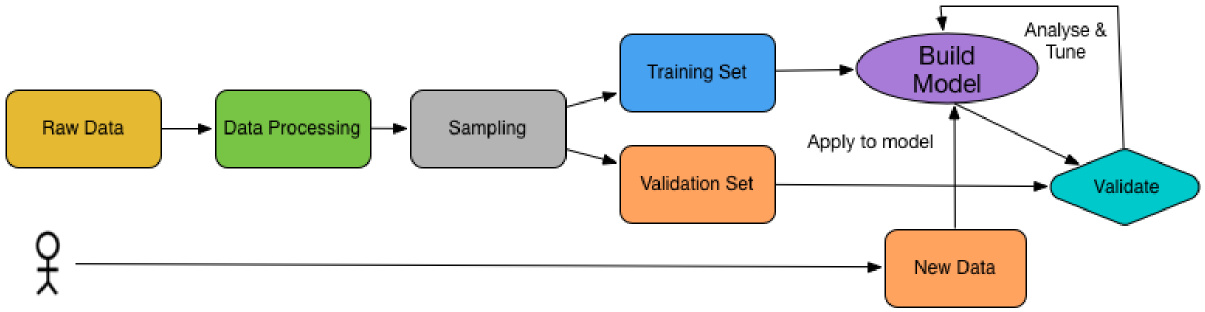

0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
−4
−3
−2
−1
0
1
2
3
4
● ● Original data

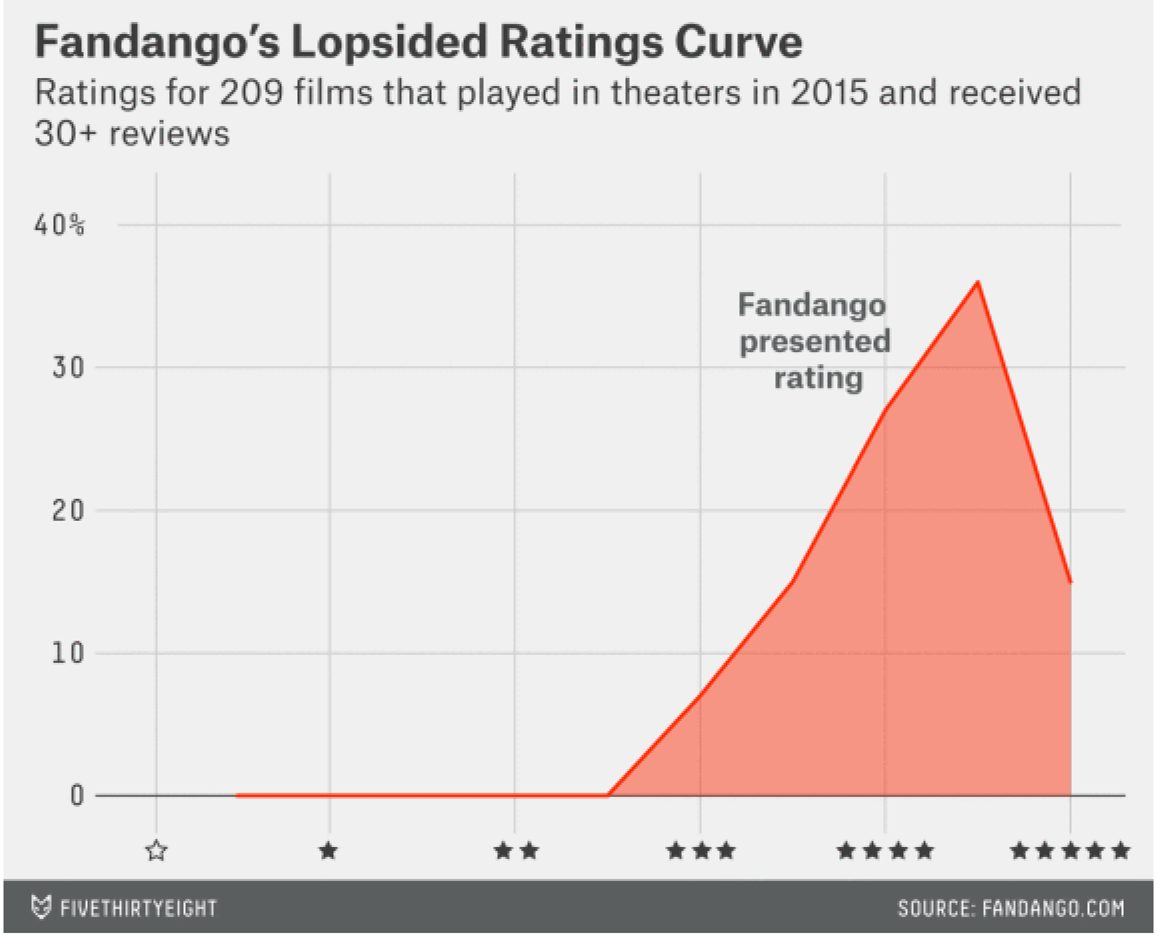

Original data
Y
X
0.1
0.2
0.3
0.4
0.5
0.6
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0


TensorBoard
SCALARS
IMAGES
AUDIO
GRAPHS
Fit to screen
Download PNG
Run
(1)
Session runs (0)
Upload
Choose File
Trace inputs
Color
Structure
Device
Main Graph
Auxiliary Nodes
gradients
GradientDe...
LossFunction
LinearRegressi...
GradientDe...
init
LinearRegr...
gradients
GradientDesc...
init
LinearRegr...

Chapter 04: Putting Data in Place Supervised Learning for Predictive Analytics



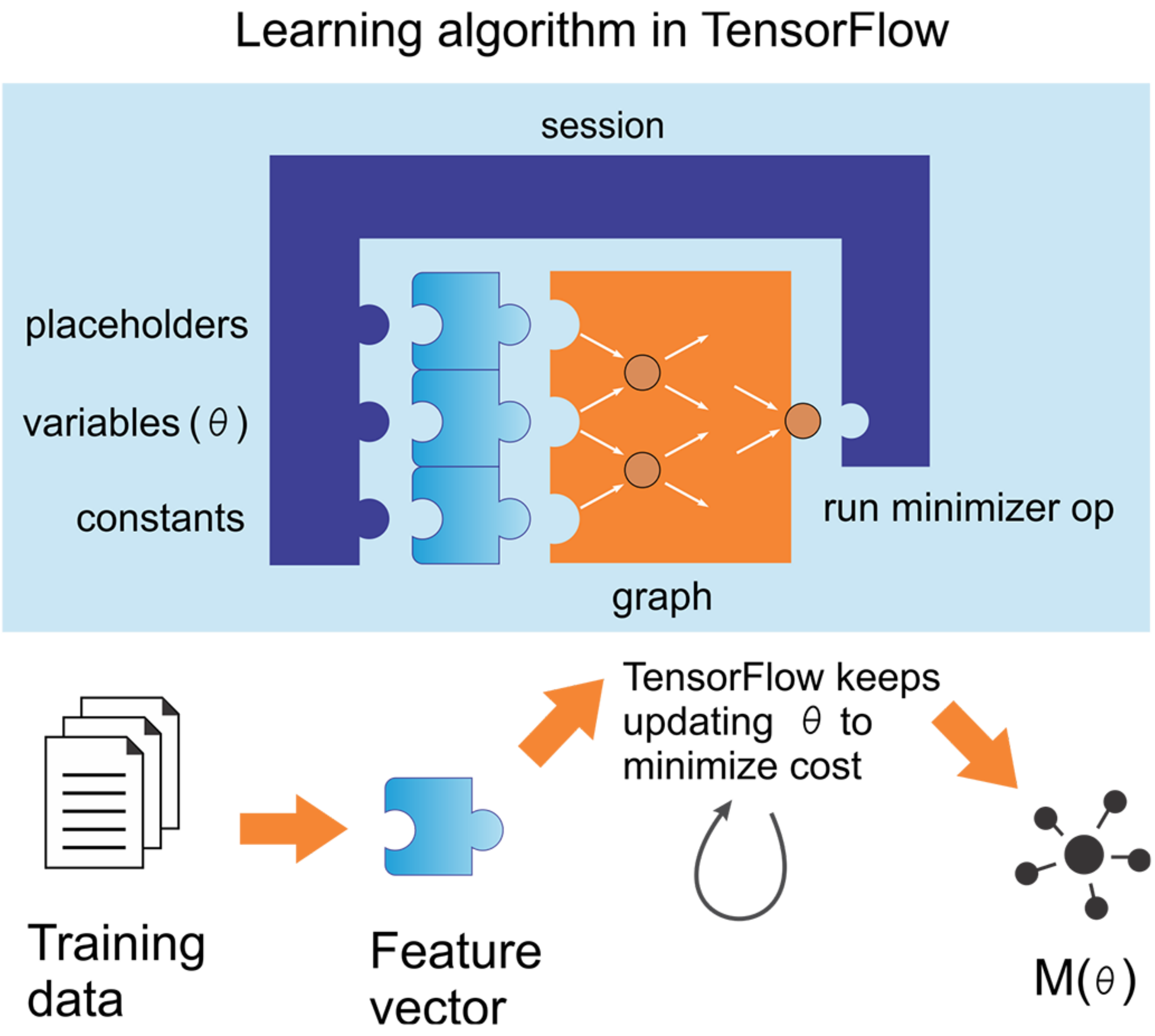


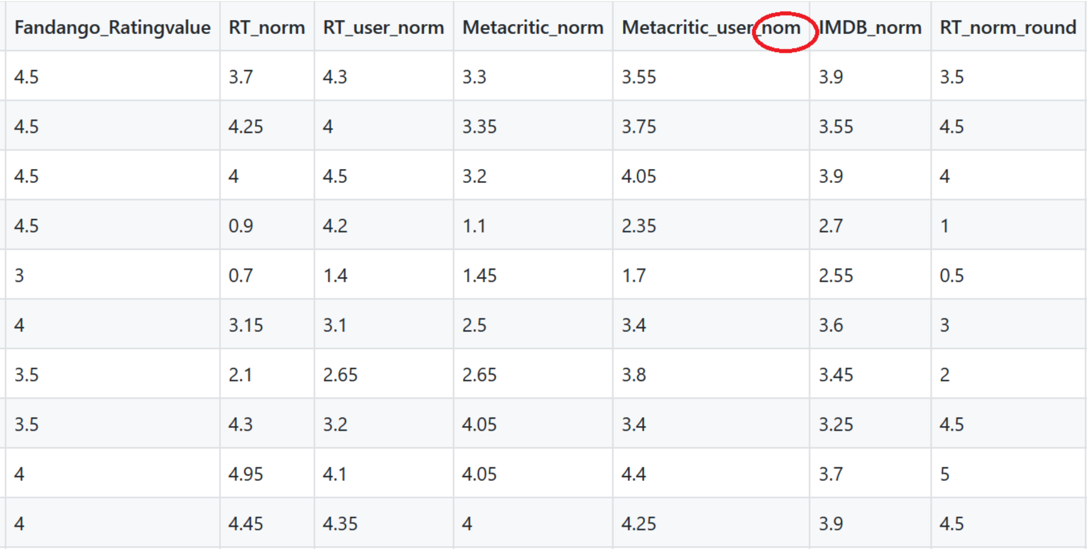


Fandango's Lopsided Ratings Curve

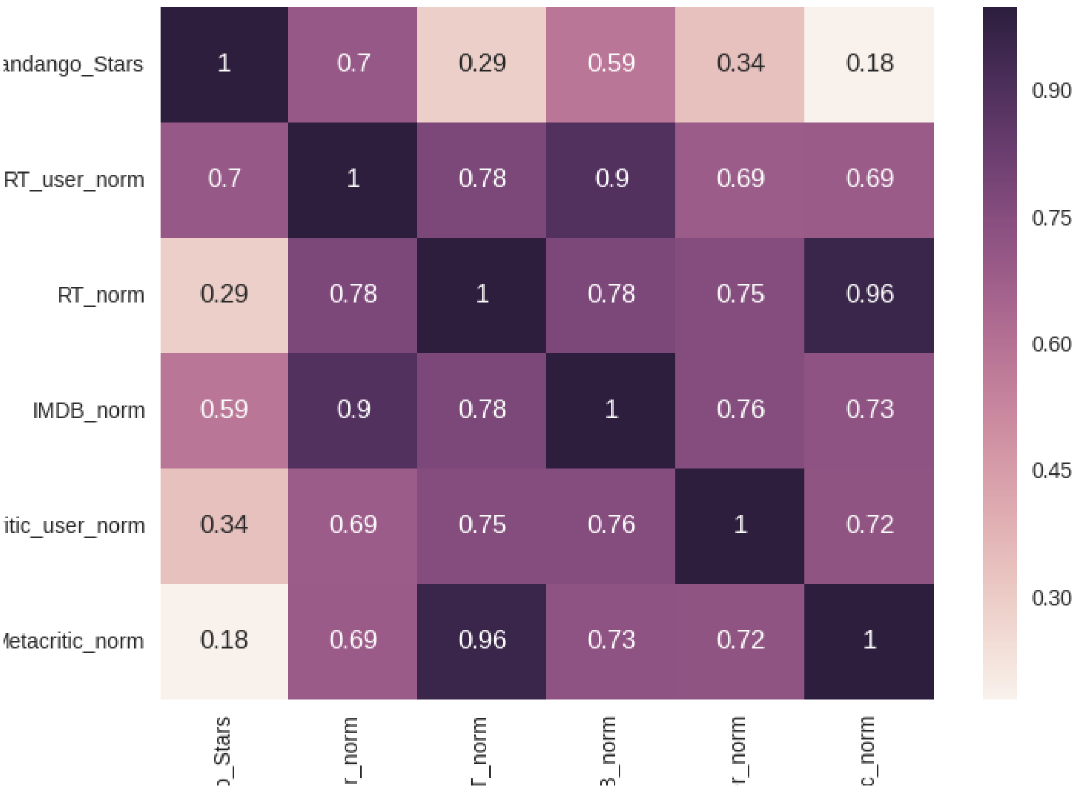
Ratings for 209 films that played in theaters in 2015 and received 30+ reviews

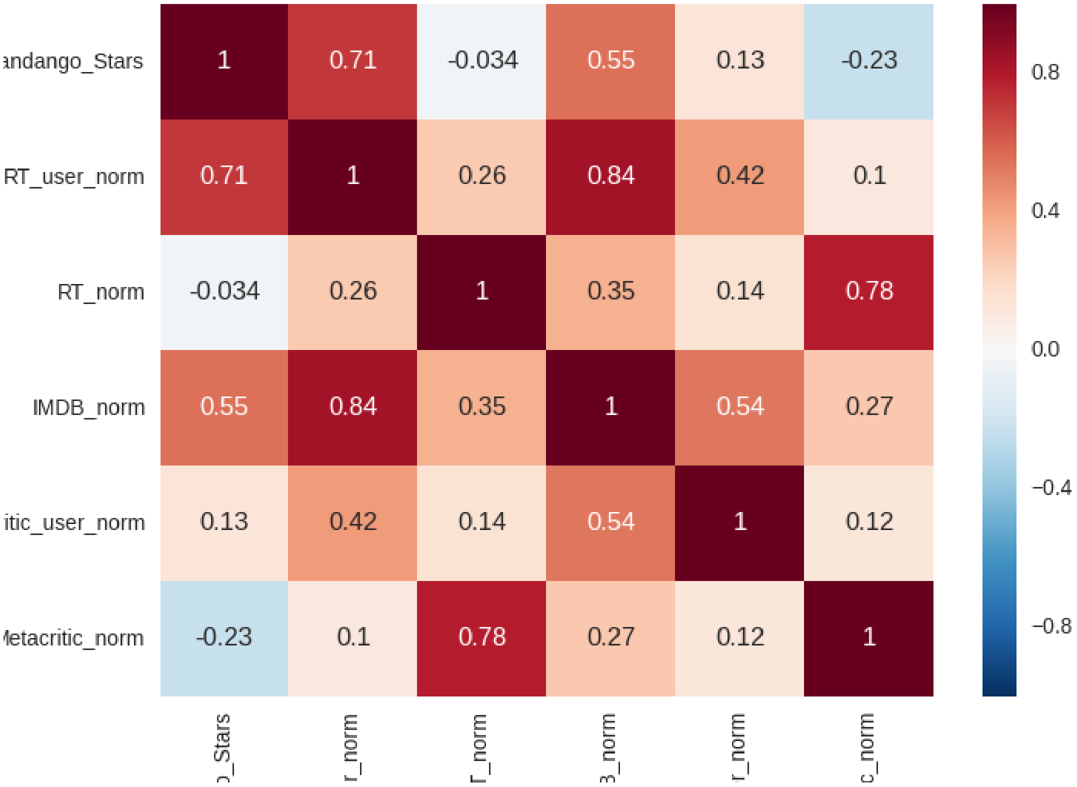
SOURCE: FANDANGO.COM

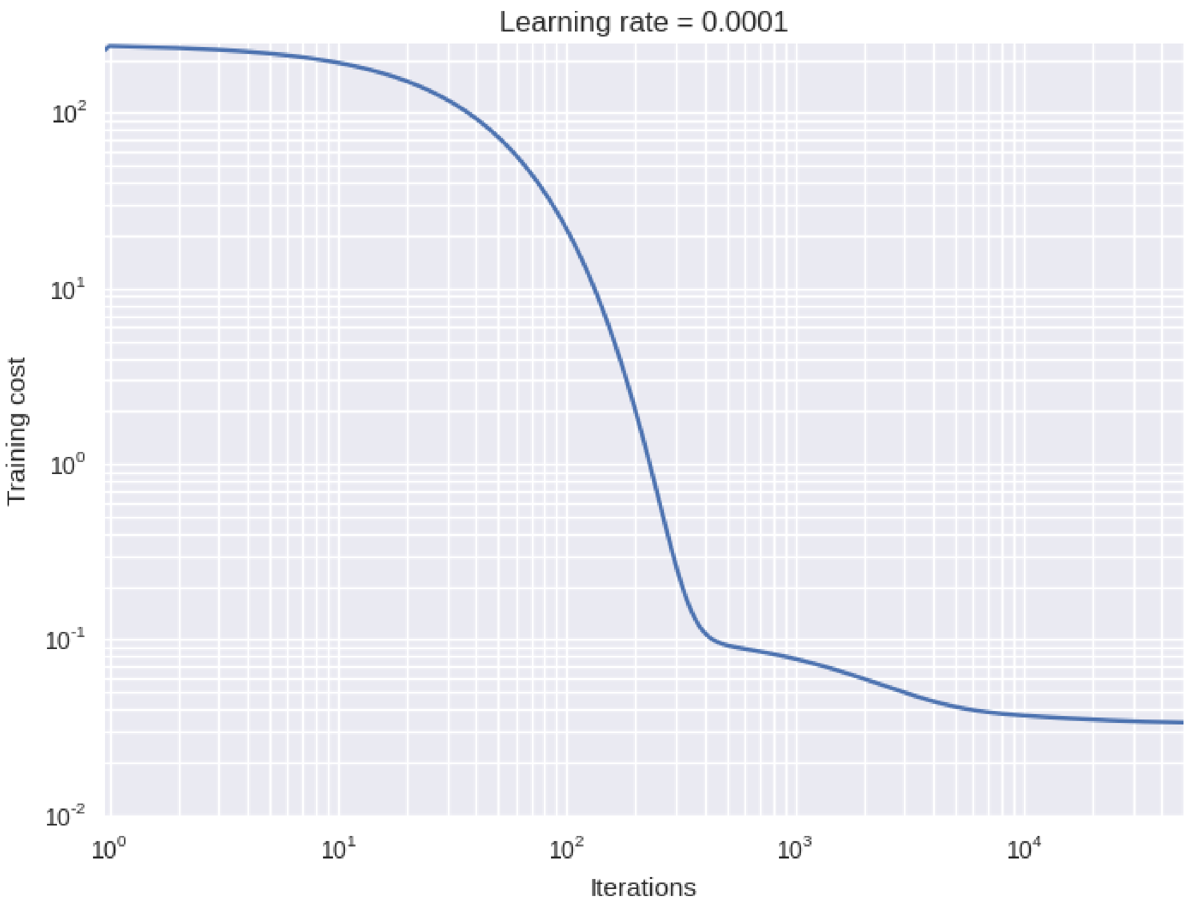

Learning algorithm in TensorFlow
session
placeholders
variables (θ)
constants
run minimizer op
graph
TensorFlow keeps updating θ to minimize cost
Training data
Feature vector
M(θ)

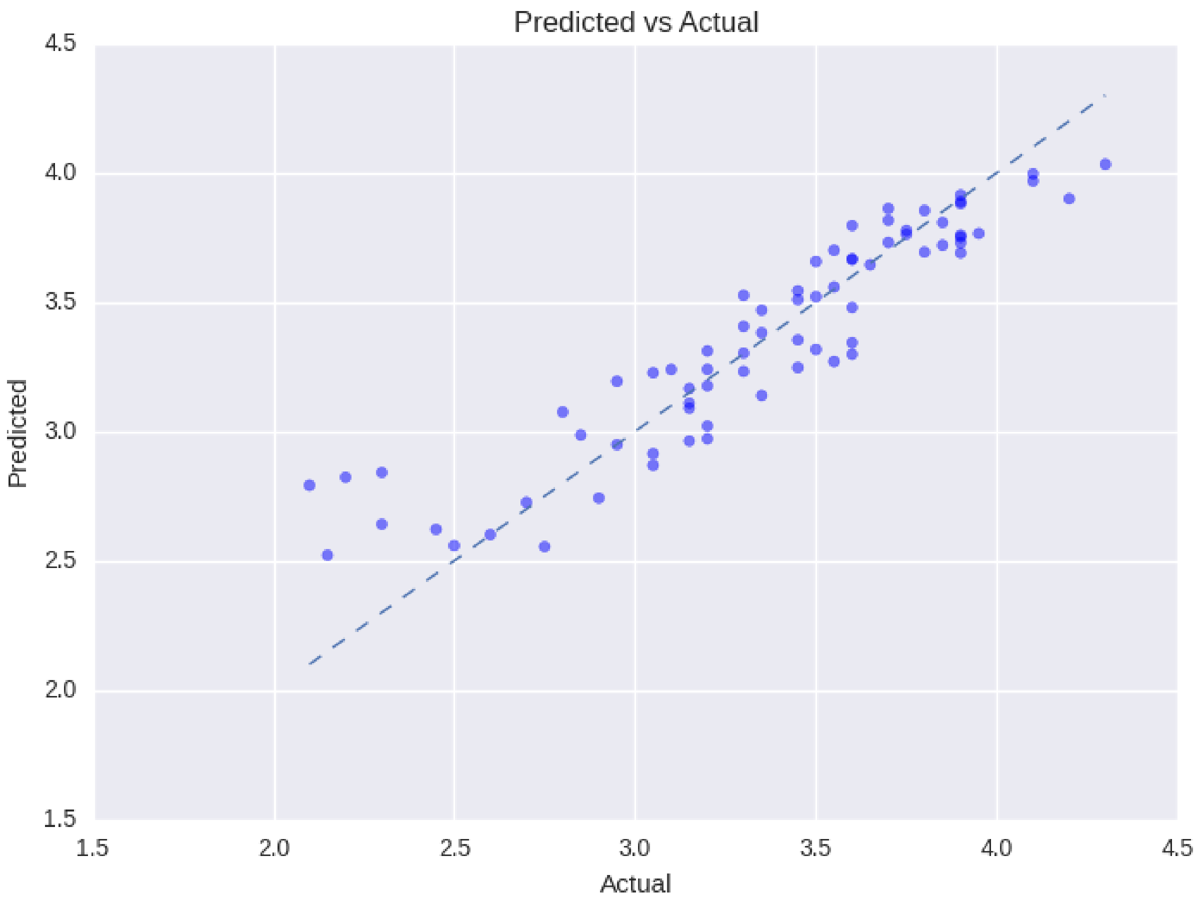


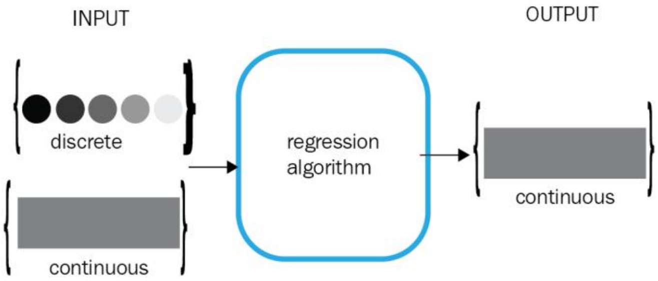
Fandango_Ratingvalue	RT_norm	RT_user_norm	Metacritic_norm	Metacritic_user_nom	IMDB_norm	RT_norm_round
4.5	3.7	4.3	3.3	3.55	3.9	3.5
4.5	4.25	4	3.35	3.75	3.55	4.5
4.5	4	4.5	3.2	4.05	3.9	4
4.5	0.9	4.2	1.1	2.35	2.7	1
3	0.7	1.4	1.45	1.7	2.55	0.5
4	3.15	3.1	2.5	3.4	3.6	3
3.5	2.1	2.65	2.65	3.8	3.45	2
3.5	4.3	3.2	4.05	3.4	3.25	4.5
4	4.95	4.1	4.05	4.4	3.7	5
4	4.45	4.35	4	4.25	3.9	4.5

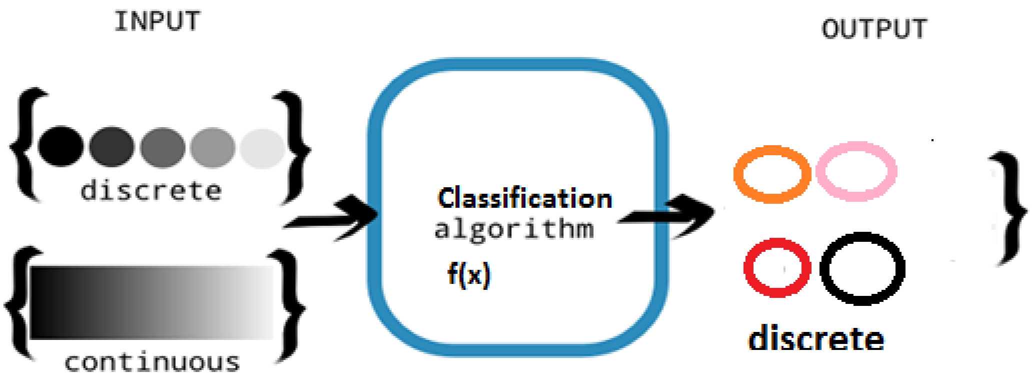

andango_Stars
RT_user_norm
RT_norm
IMDB_norm
itic_user_norm
letacritic_norm
1 0.7 0.29 0.59 0.34 0.18
0.7 1 0.78 0.9 0.69 0.69
0.29 0.78 1 0.78 0.75 0.96
0.59 0.9 0.78 1 0.76 0.73
0.34 0.69 0.75 0.76 1 0.72
0.18 0.69 0.96 0.73 0.72 1
o_Stars
r_norm
T_norm
3_norm
r_norm
c_norm
0.90
0.75
0.60
0.45
0.30

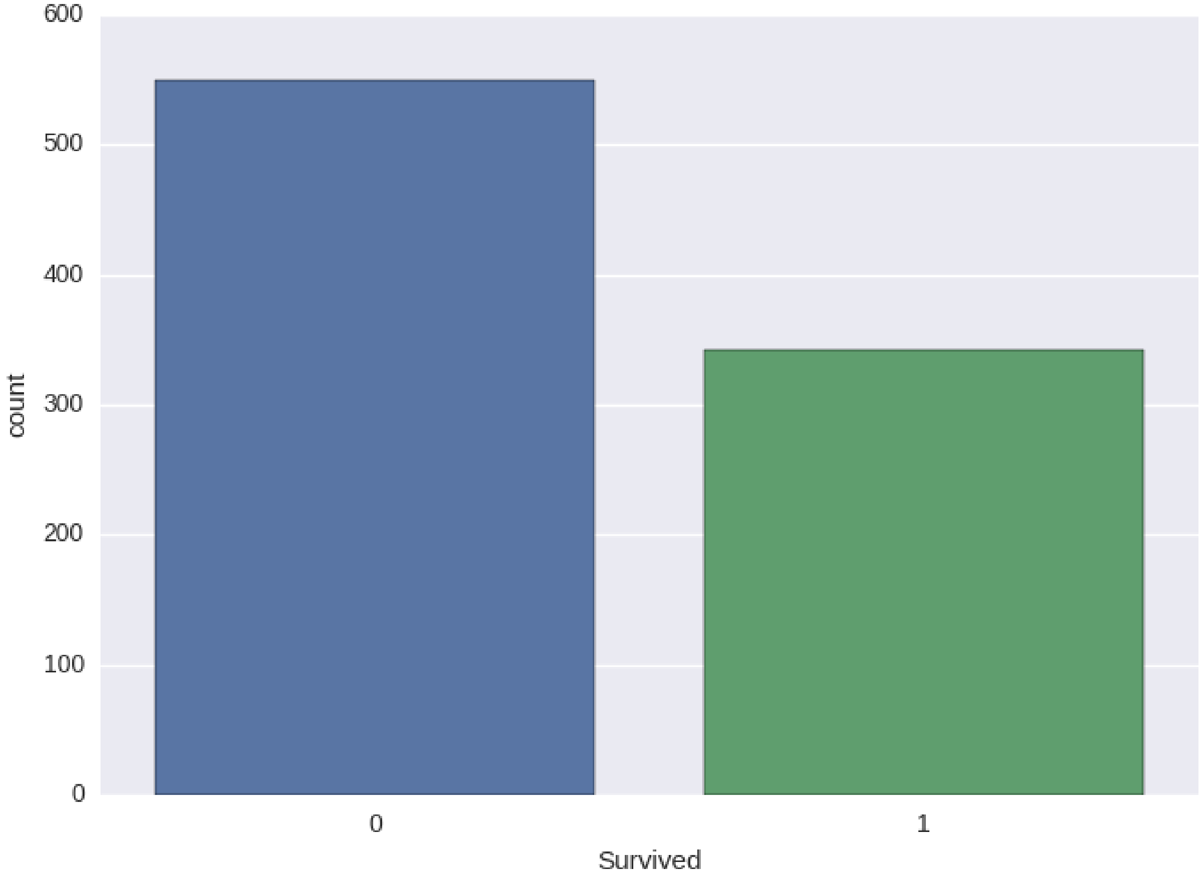

andango_Stars
RT_user_norm
RT_norm
IMDB_norm
itic_user_norm
letacritic_norm
1
0.71
-0.034
0.55
0.13
-0.23
0.71
1
0.26
0.84
0.42
0.1
-0.034
0.26
1
0.35
0.14
0.78
0.55
0.84
0.35
1
0.54
0.27
0.13
0.42
0.14
0.54
1
0.12
-0.23
0.1
0.78
0.27
0.12
1
o_Stars
r_norm
T_norm
3_norm
r_norm
c_norm
0.8
0.4
0.0
−0.4
−0.8

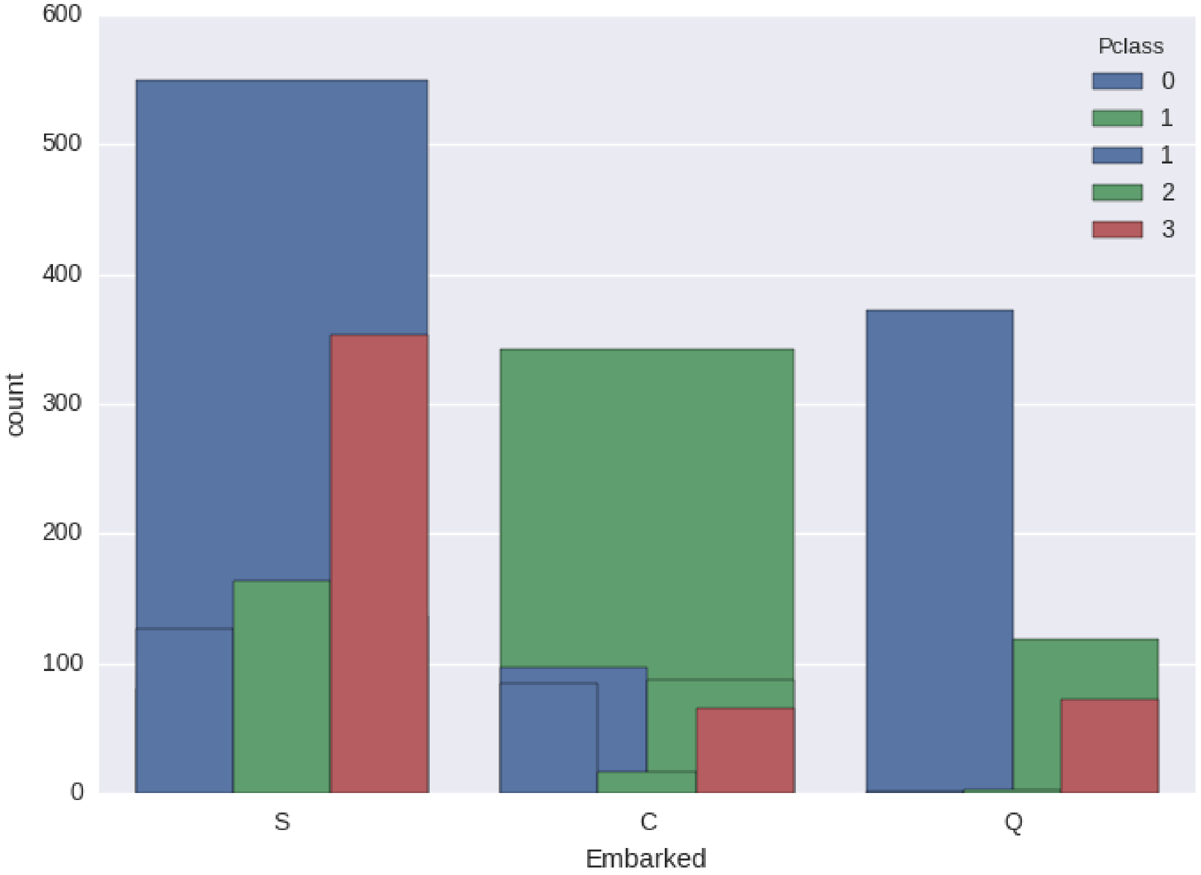

Learning rate = 0.0001
Training cost
10^{2}
10^{1}
10^{0}
10^{-1}
10^{-2}
10^{0}
10^{1}
10^{2}
10^{3}
10^{4}
Iterations


Predicted vs Actual
Predicted
Actual
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.5
2.0
2.5
3.0
3.5
4.0
4.5

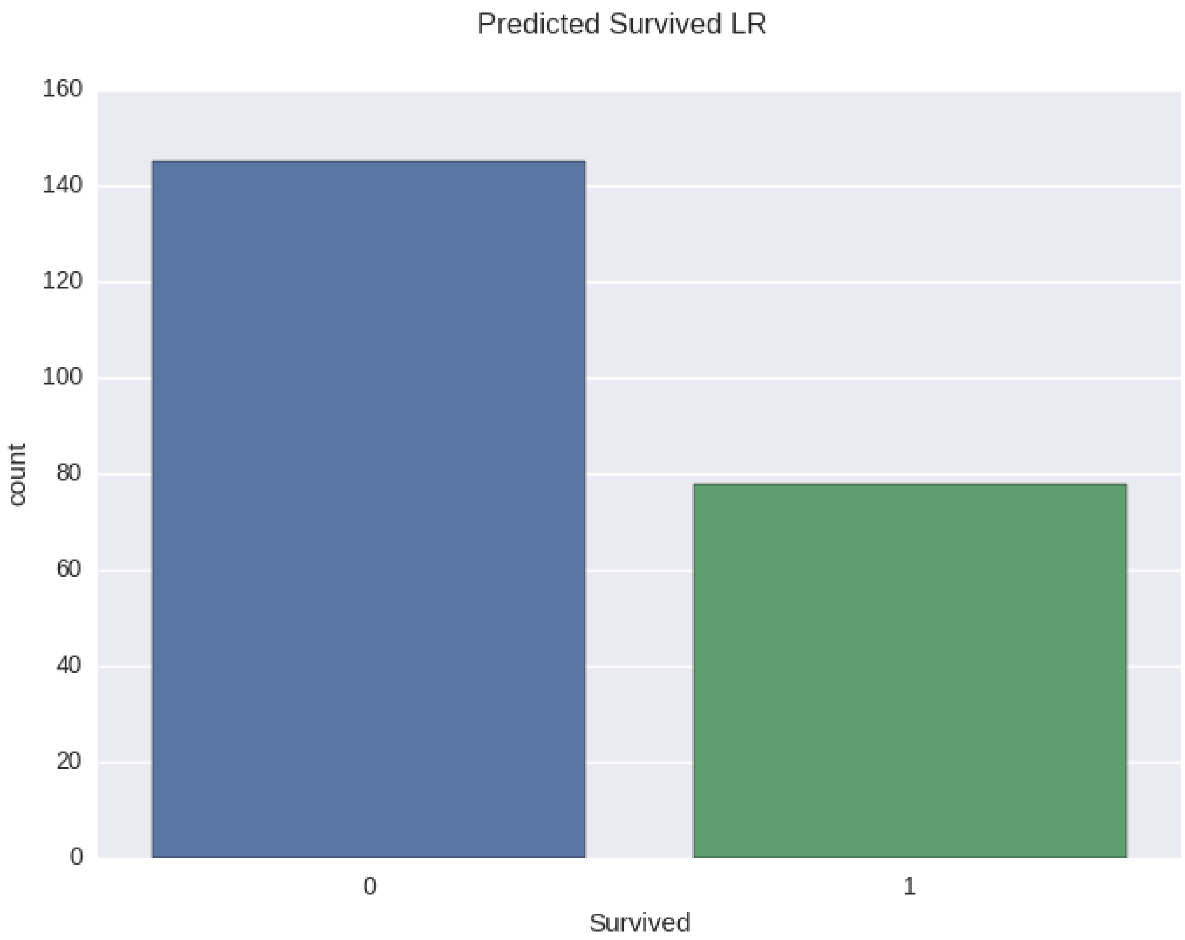

INPUT
discrete
continuous
regression algorithm
OUTPUT
continuous

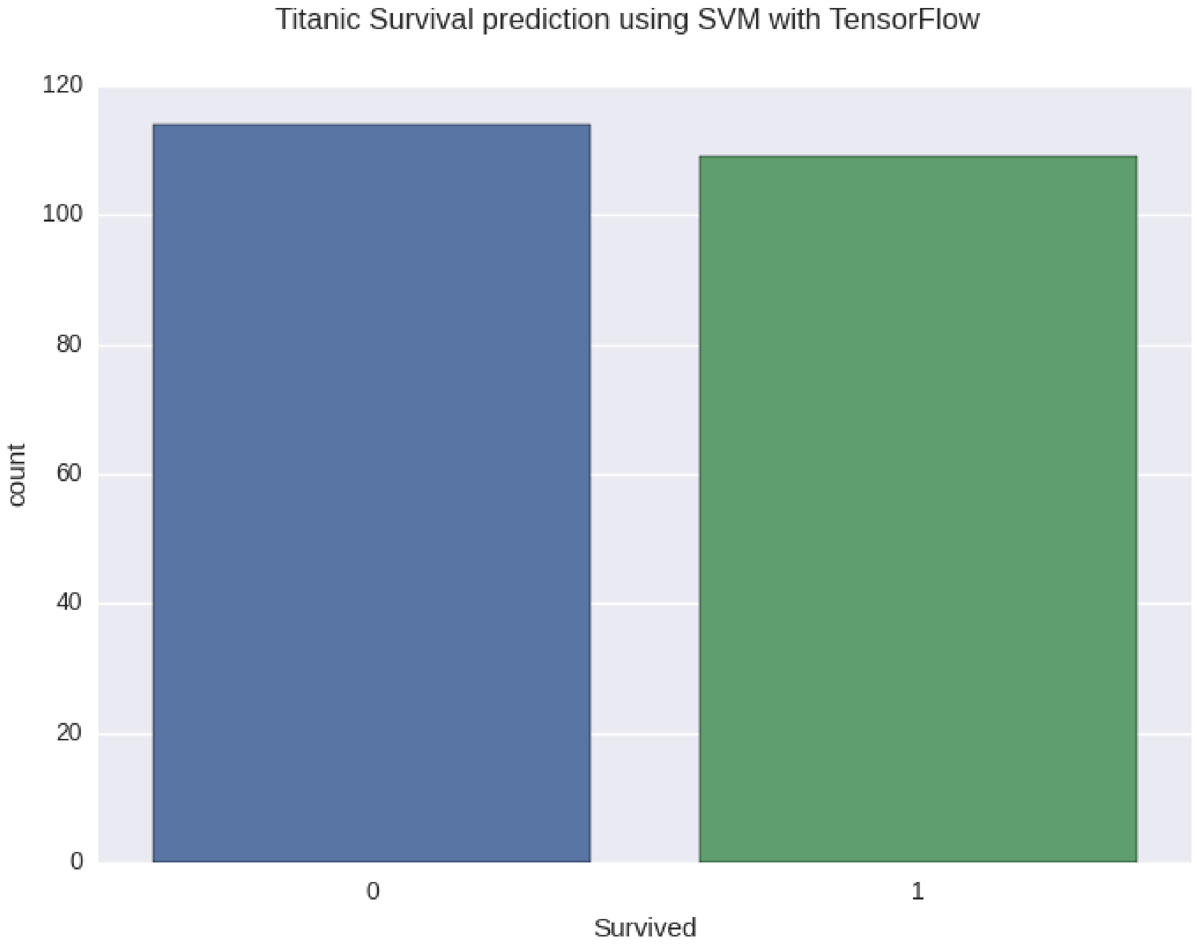

INPUT
discrete
continuous
Classification
algorithm
f(x)
OUTPUT
discrete

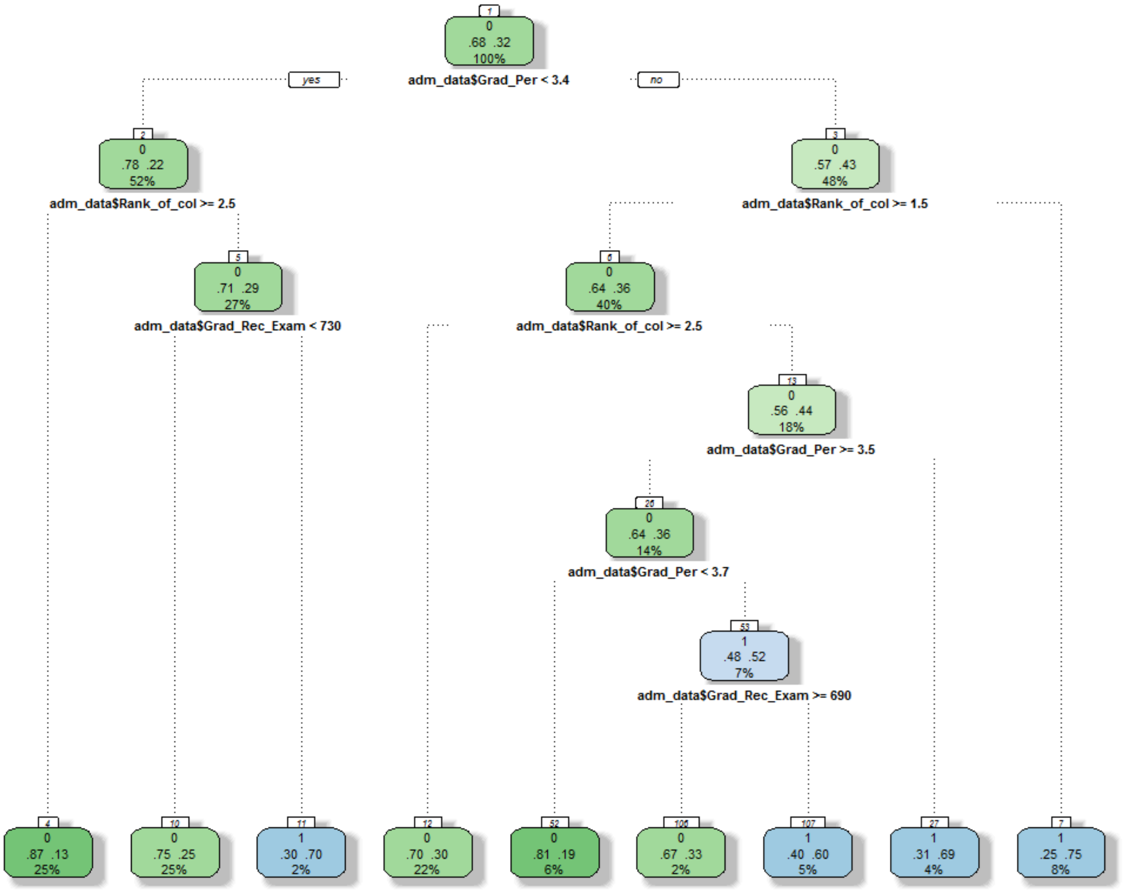

600
500
400
300
200
100
0
count
0
1
Survived



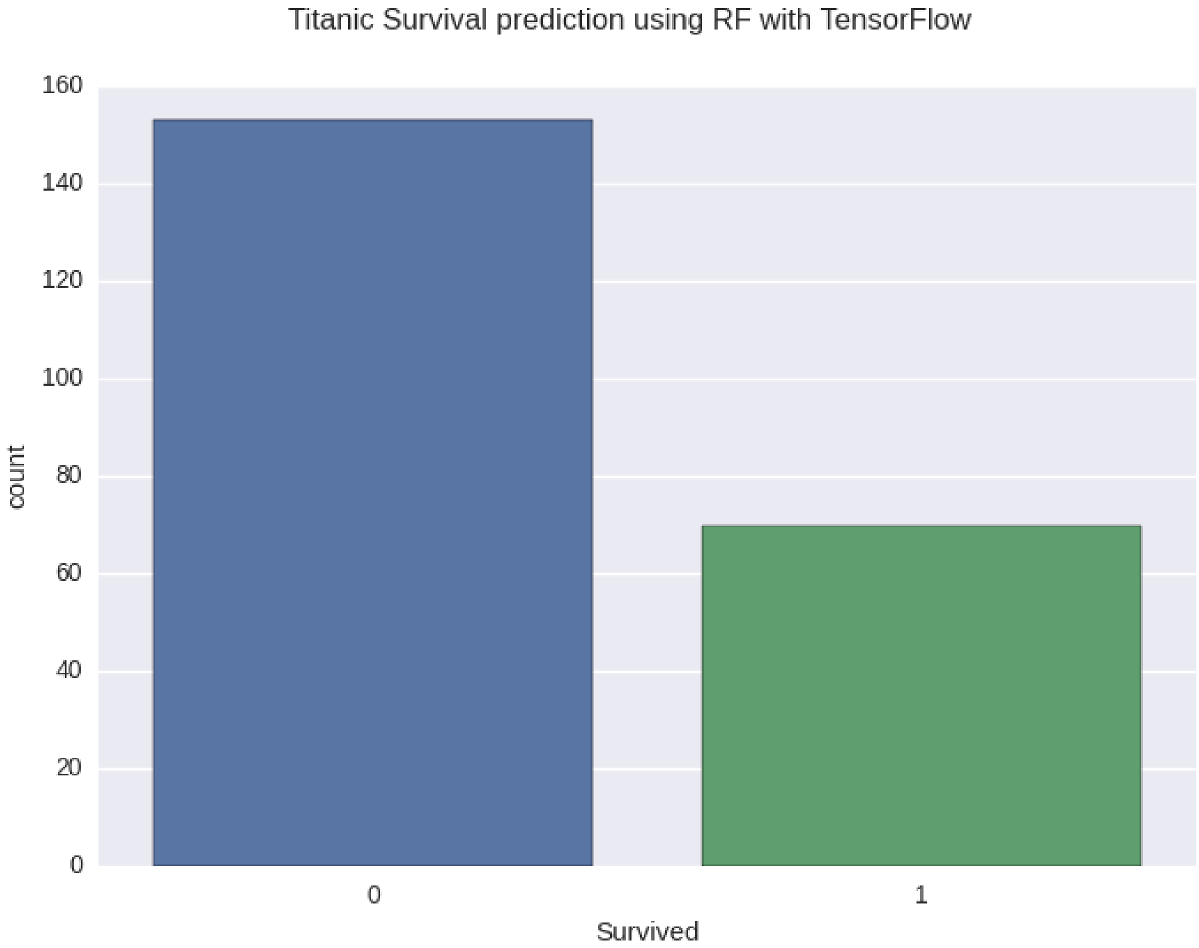
600
500
400
300
200
100
0
count
S
C
Q
Embarked
Pclass
0
1
1
2
3


Predicted Survived LR
count
160
140
120
100
80
60
40
20
0
0
1
Survived

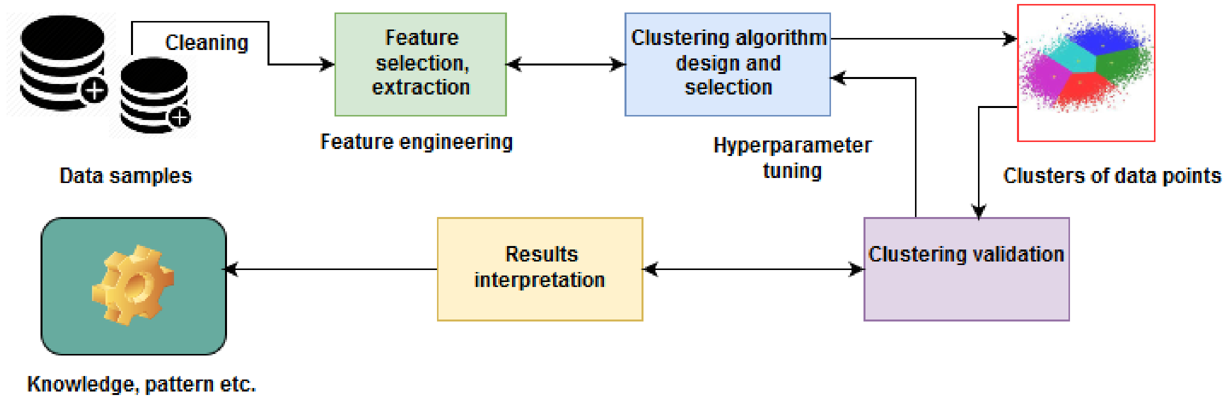

Titanic Survival prediction using SVM with TensorFlow
120
100
80
60
40
20
0
count
0
1
Survived

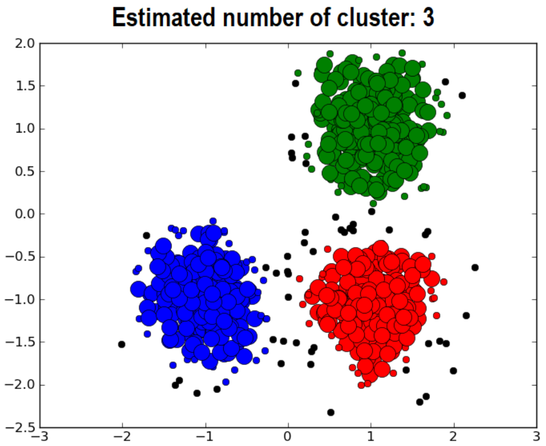


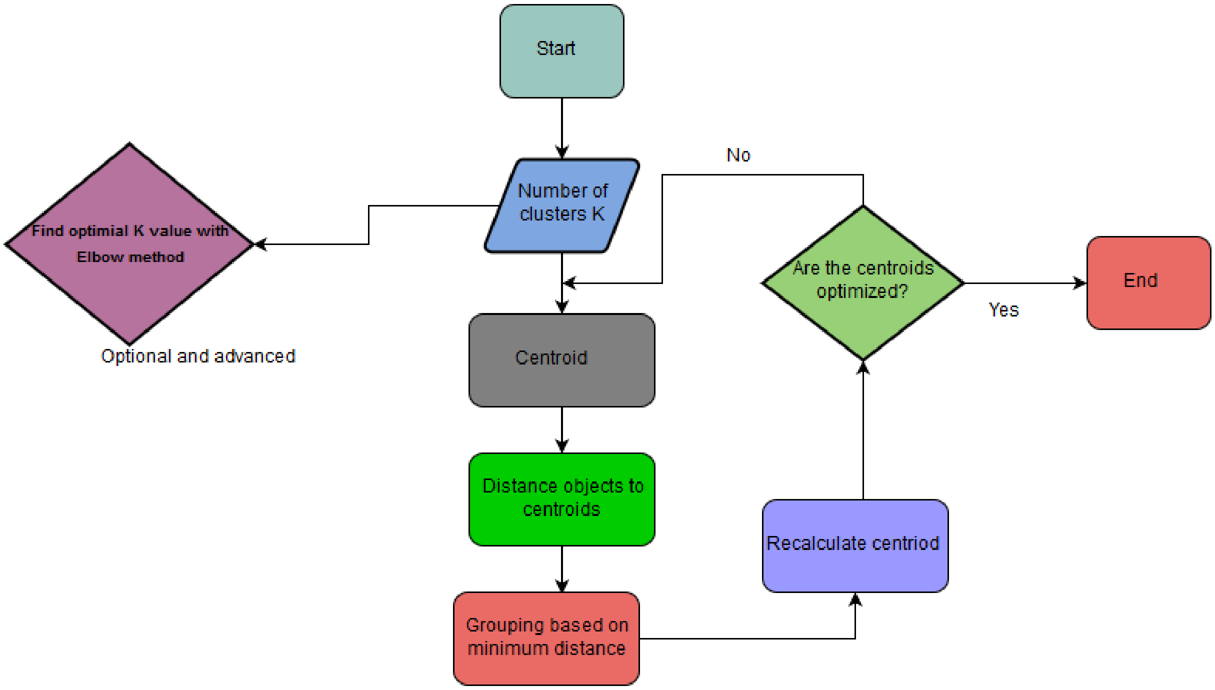
Rattle 2017-Jan-14 14:45:30 rezkar


Titanic Survival prediction using RF with TensorFlow
160
140
120
100
80
60
40
20
0
count
0
1
Survived

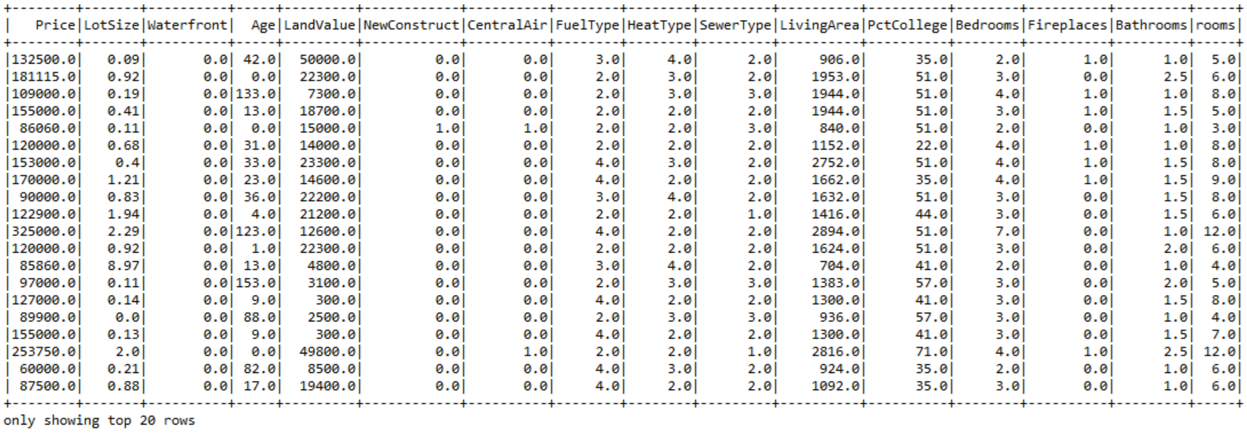
Chapter 05: Clustering Your Data Unsupervised Learning for Predictive Analytics



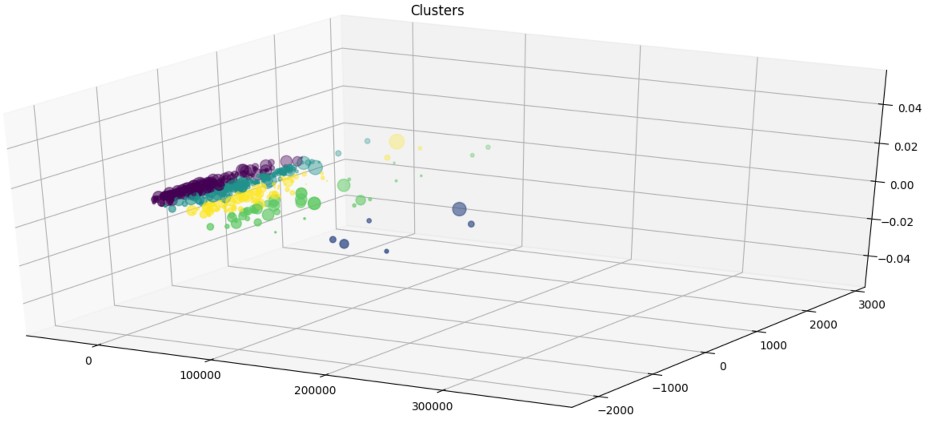


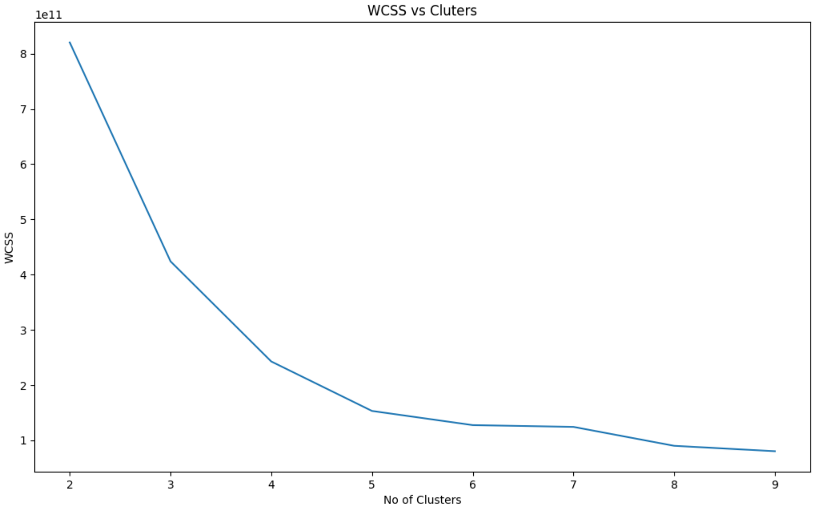


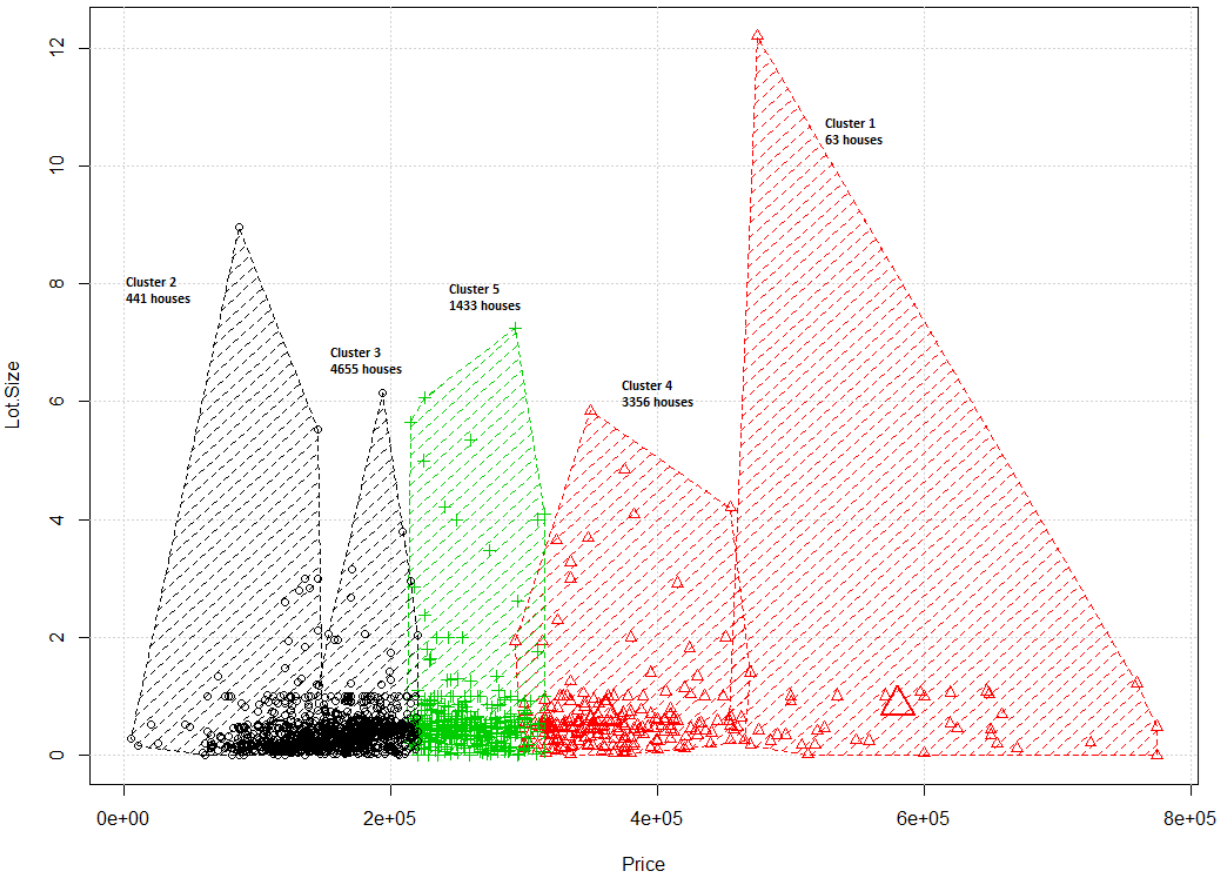
Start
Number of clusters K
Find optimial K value with Elbow method
Optional and advanced
No
Are the centroids optimized?
Yes
End
Centroid
Distance objects to centroids
Grouping based on minimum distance
Recalculate centriod

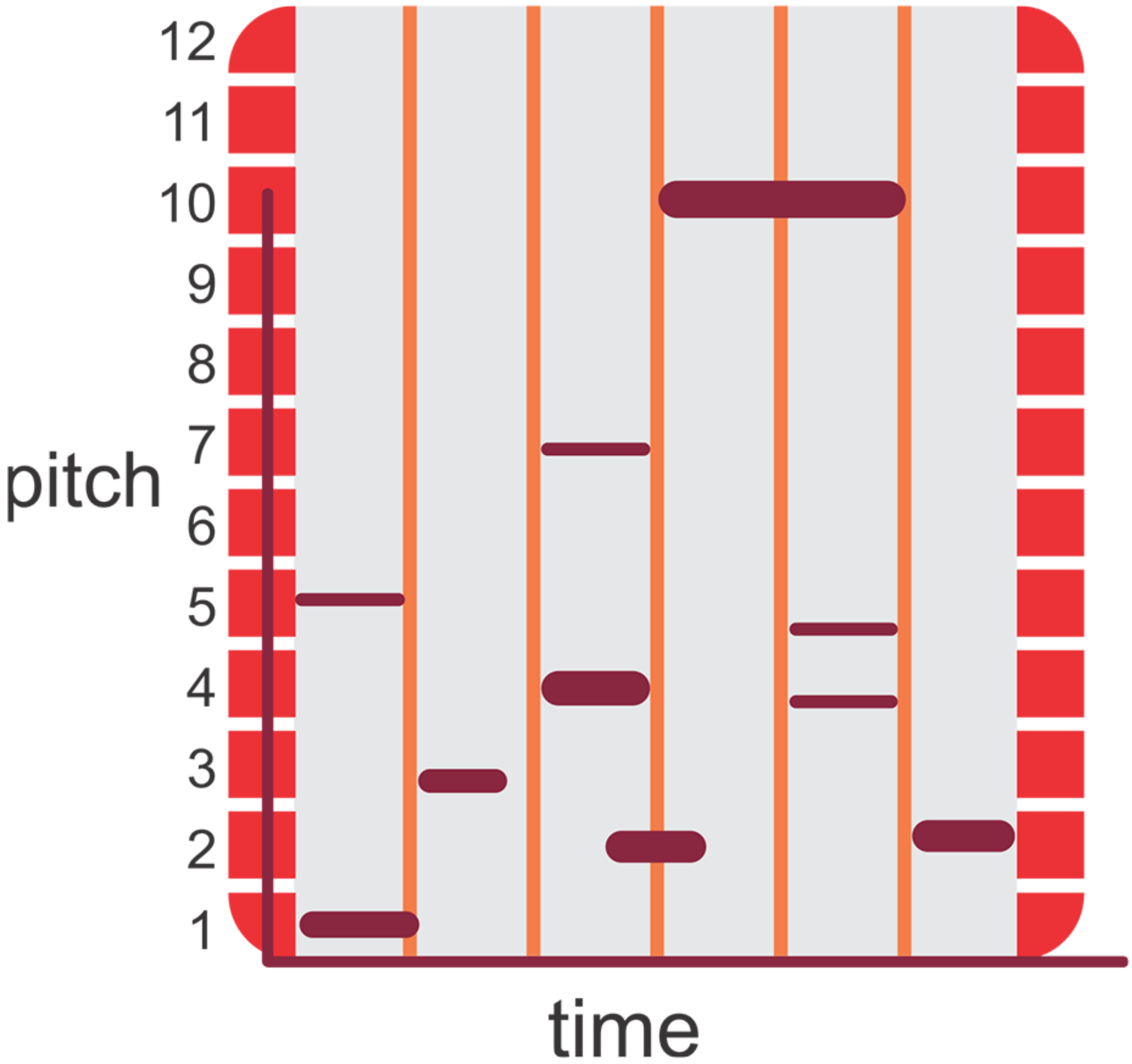


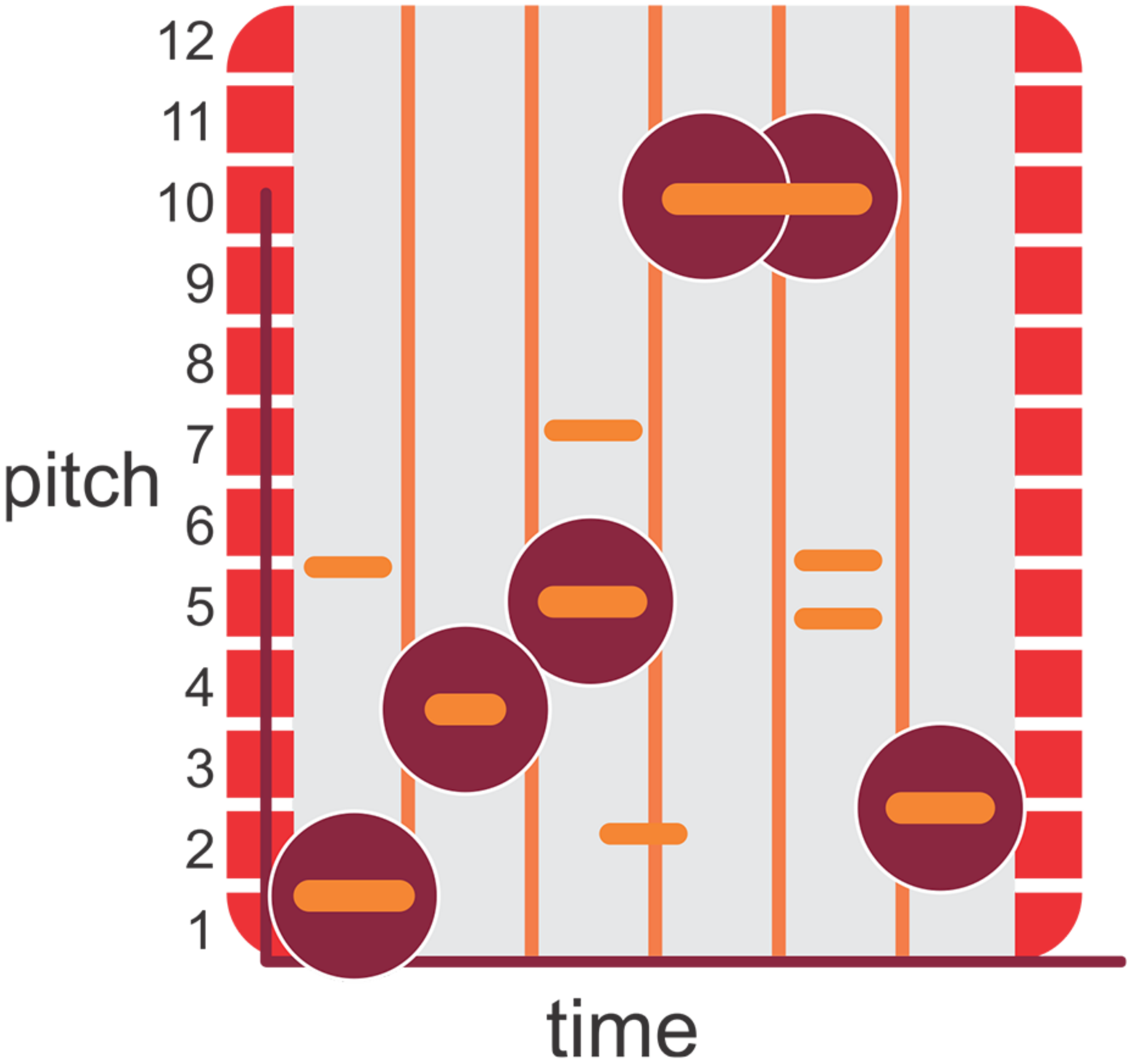
```
+--------+-------+----------+-----+---------+------------+----------+--------+--------+---------+----------+----------+--------+----------+---------+-----+
|   Price|LotSize|Waterfront|  Age|LandValue|NewConstruct|CentralAir|FuelType|HeatType|SewerType|LivingArea|PctCollege|Bedrooms|Fireplaces|Bathrooms|rooms|
+--------+-------+----------+-----+---------+------------+----------+--------+--------+---------+----------+----------+--------+----------+---------+-----+
|132500.0|   0.09|       0.0| 42.0|  50000.0|         0.0|       0.0|     3.0|     4.0|      2.0|     906.0|      35.0|     2.0|       1.0|      1.0|  5.0|
|181115.0|   0.92|       0.0|  0.0|  22300.0|         0.0|       0.0|     2.0|     3.0|      2.0|    1953.0|      51.0|     3.0|       0.0|      2.5|  6.0|
|109000.0|   0.19|       0.0|133.0|   7300.0|         0.0|       0.0|     2.0|     3.0|      3.0|    1944.0|      51.0|     4.0|       1.0|      1.0|  8.0|
|155000.0|   0.41|       0.0| 13.0|  18700.0|         0.0|       0.0|     2.0|     2.0|      2.0|    1944.0|      51.0|     3.0|       1.0|      1.5|  5.0|
| 86060.0|   0.11|       0.0|  0.0|  15000.0|         1.0|       1.0|     2.0|     2.0|      3.0|     840.0|      51.0|     2.0|       0.0|      1.0|  3.0|
|120000.0|   0.68|       0.0| 31.0|  14000.0|         0.0|       0.0|     2.0|     2.0|      2.0|    1152.0|      22.0|     4.0|       1.0|      1.0|  8.0|
|153000.0|    0.4|       0.0| 33.0|  23300.0|         0.0|       0.0|     4.0|     3.0|      2.0|    2752.0|      51.0|     4.0|       1.0|      1.5|  8.0|
|170000.0|   1.21|       0.0| 23.0|  14600.0|         0.0|       0.0|     4.0|     2.0|      2.0|    1662.0|      35.0|     4.0|       1.0|      1.5|  9.0|
| 90000.0|   0.83|       0.0| 36.0|  22200.0|         0.0|       0.0|     3.0|     4.0|      2.0|    1632.0|      51.0|     3.0|       0.0|      1.5|  8.0|
|122900.0|   1.94|       0.0|  4.0|  21200.0|         0.0|       0.0|     2.0|     2.0|      1.0|    1416.0|      44.0|     3.0|       0.0|      1.5|  6.0|
|325000.0|   2.29|       0.0|123.0|  12600.0|         0.0|       0.0|     4.0|     2.0|      2.0|    2894.0|      51.0|     7.0|       0.0|      1.0| 12.0|
|120000.0|   0.92|       0.0|  1.0|  22300.0|         0.0|       0.0|     2.0|     2.0|      2.0|    1624.0|      51.0|     3.0|       0.0|      2.0|  6.0|
| 85860.0|   8.97|       0.0| 13.0|   4800.0|         0.0|       0.0|     3.0|     4.0|      2.0|     704.0|      41.0|     2.0|       0.0|      1.0|  4.0|
| 97000.0|   0.11|       0.0|153.0|   3100.0|         0.0|       0.0|     2.0|     3.0|      3.0|    1383.0|      57.0|     3.0|       0.0|      2.0|  5.0|
|127000.0|   0.14|       0.0|  9.0|    300.0|         0.0|       0.0|     4.0|     2.0|      2.0|    1300.0|      41.0|     3.0|       0.0|      1.5|  8.0|
| 89900.0|    0.0|       0.0| 88.0|   2500.0|         0.0|       0.0|     2.0|     3.0|      3.0|     936.0|      57.0|     3.0|       0.0|      1.0|  4.0|
|155000.0|   0.13|       0.0|  9.0|    300.0|         0.0|       0.0|     4.0|     2.0|      2.0|    1300.0|      41.0|     3.0|       0.0|      1.5|  7.0|
|253750.0|    2.0|       0.0|  0.0|  49800.0|         0.0|       1.0|     2.0|     2.0|      1.0|    2816.0|      71.0|     4.0|       1.0|      2.5| 12.0|
| 60000.0|   0.21|       0.0| 82.0|   8500.0|         0.0|       0.0|     4.0|     3.0|      2.0|     924.0|      35.0|     2.0|       0.0|      1.0|  6.0|
| 87500.0|   0.88|       0.0| 17.0|  19400.0|         0.0|       0.0|     4.0|     2.0|      2.0|    1092.0|      35.0|     3.0|       0.0|      1.0|  6.0|
+--------+-------+----------+-----+---------+------------+----------+--------+--------+---------+----------+----------+--------+----------+---------+-----+
only showing top 20 rows
```

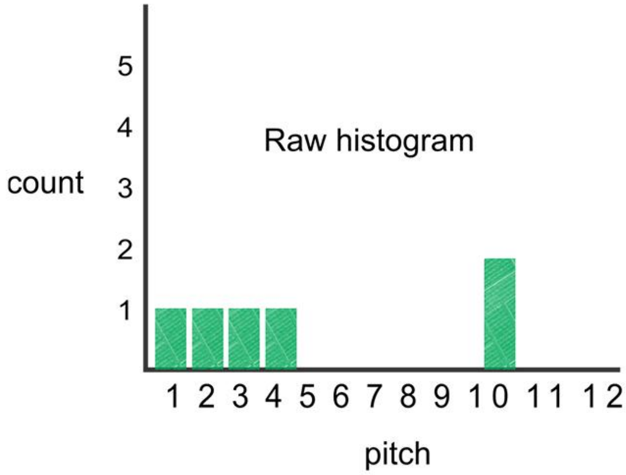

Clusters
0
100000
200000
300000
−2000
−1000
0
1000
2000
3000
−0.04
−0.02
0.00
0.02
0.04

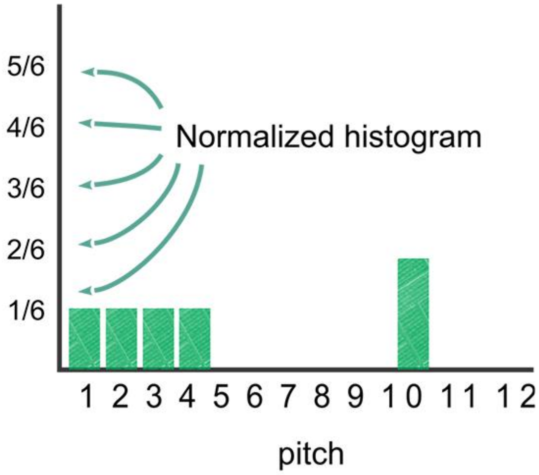

WCSS vs Cluters
1e11
WCSS
8
7
6
5
4
3
2
1
2
3
4
5
6
7
8
9
No of Clusters

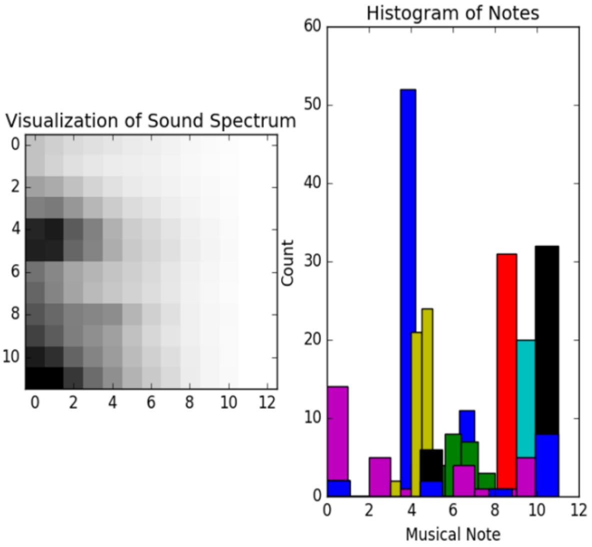

Cluster 1
63 houses
Cluster 2
441 houses
Cluster 3
4655 houses
Cluster 4
3356 houses
Cluster 5
1433 houses
Lot.Size
0
2
4
6
8
10
12
Price
0e+00
2e+05
4e+05
6e+05
8e+05

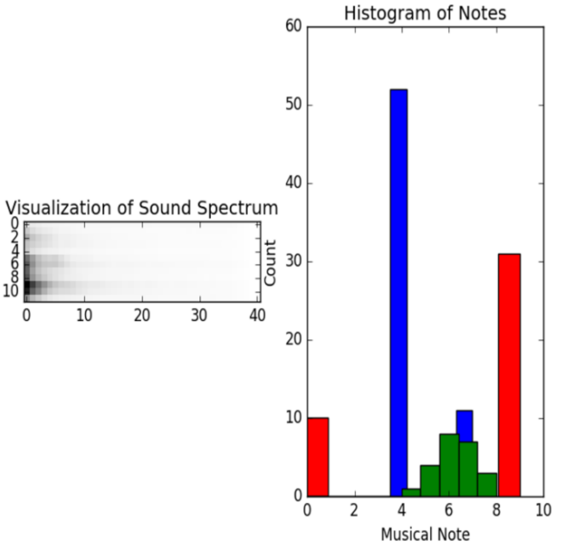

12
11
10
9
8
7
pitch
6
5
4
3
2
1
time

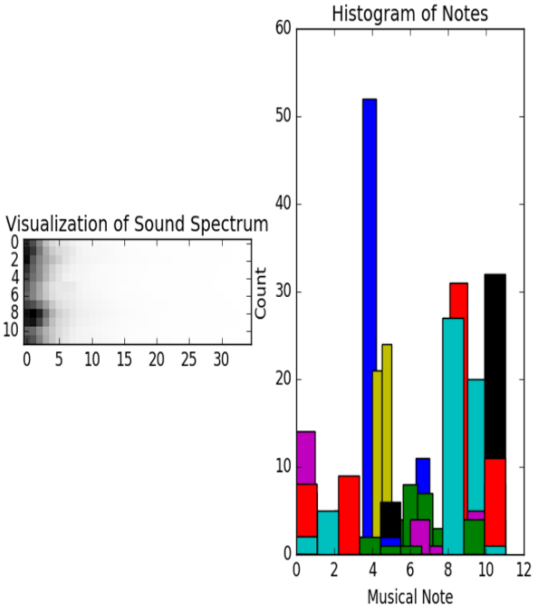

12
11
10
9
8
7
pitch
6
5
4
3
2
1
time

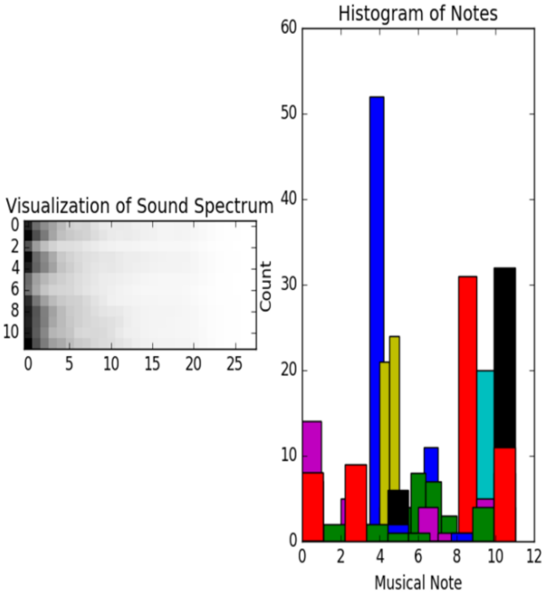

count
5
4
3
2
1
Raw histogram
1 2 3 4 5 6 7 8 9 10 11 12
pitch

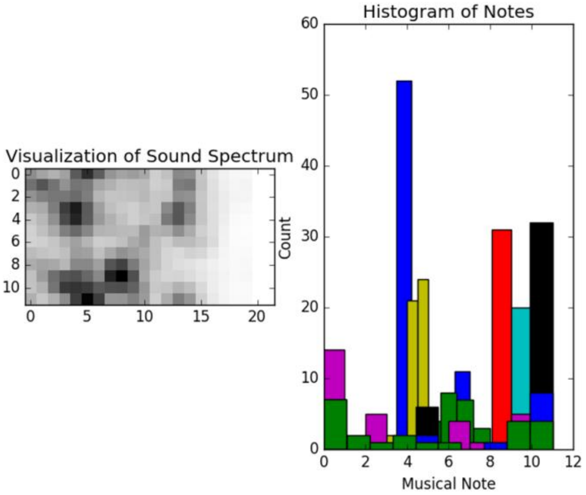

5/6
4/6
3/6
2/6
1/6
Normalized histogram
1 2 3 4 5 6 7 8 9 10 11 12
pitch

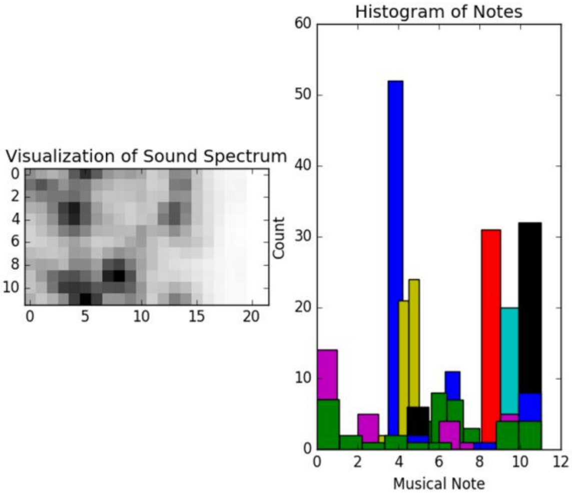

Visualization of Sound Spectrum
0
2
4
6
8
10
0 2 4 6 8 10 12
Histogram of Notes
60
50
40
30
20
10
0
Count
0 2 4 6 8 10 12
Musical Note

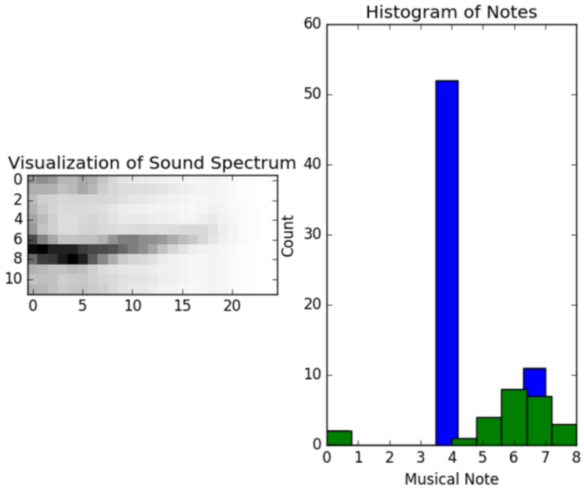

Visualization of Sound Spectrum
0
2
4
6
8
10
0 10 20 30 40
Histogram of Notes
60
50
40
30
20
10
0
Count
0 2 4 6 8 10
Musical Note

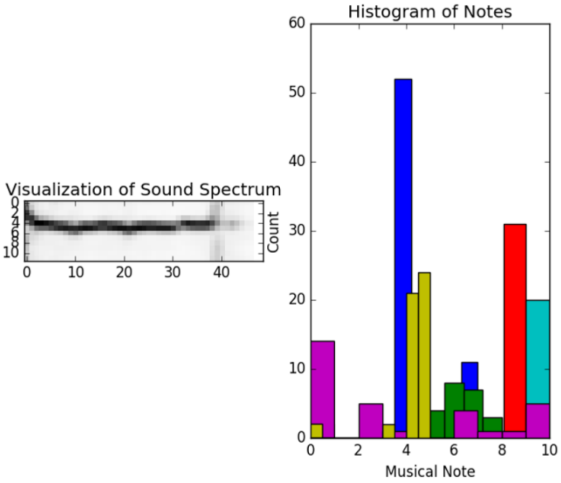

Visualization of Sound Spectrum
0 2 4 6 8 10
0 5 10 15 20 25 30
Histogram of Notes
Count
0 10 20 30 40 50 60
0 2 4 6 8 10 12
Musical Note

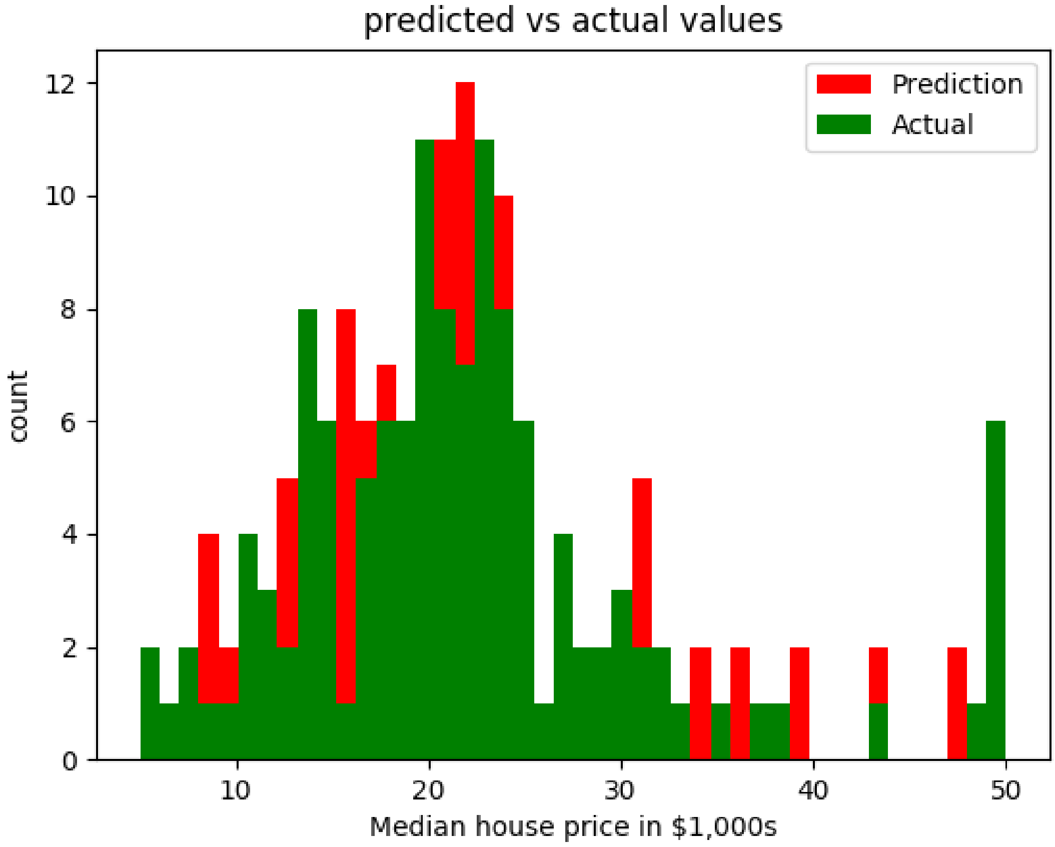

Visualization of Sound Spectrum
0 2 4 6 8 10
0 5 10 15 20 25
Histogram of Notes
Count
0 10 20 30 40 50 60
0 2 4 6 8 10 12
Musical Note


Visualization of Sound Spectrum
0 2 4 6 8 10
0 5 10 15 20
Histogram of Notes
Count
0 10 20 30 40 50 60
0 2 4 6 8 10 12
Musical Note

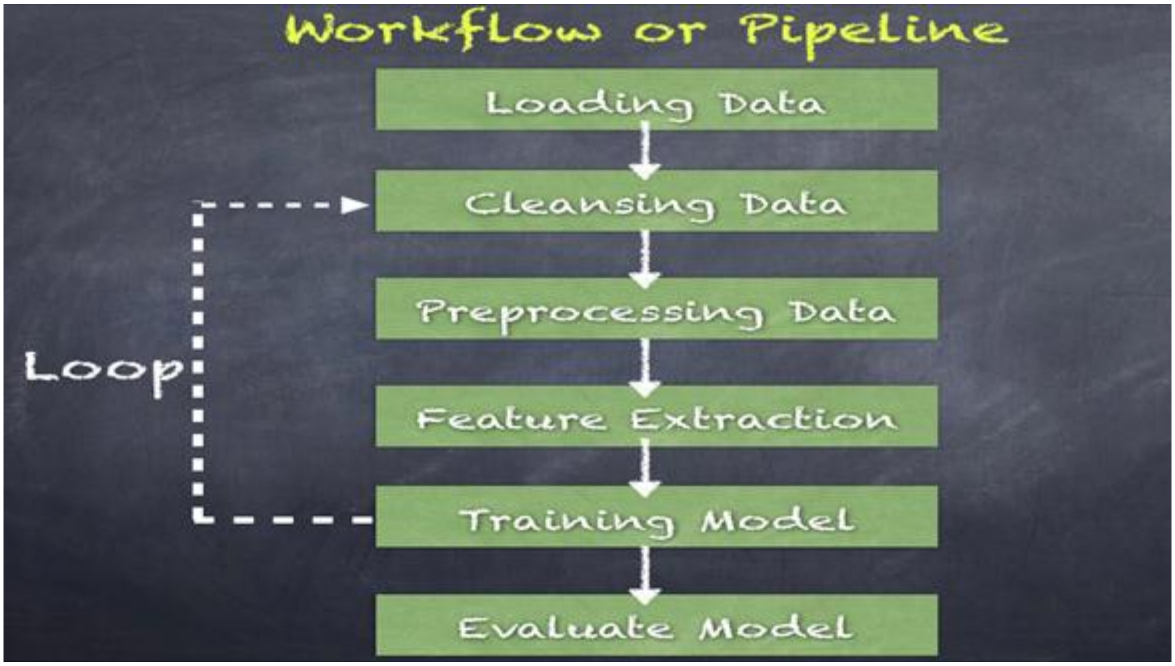

Visualization of Sound Spectrum
0 2 4 6 8 10
0 5 10 15 20
Histogram of Notes
Count
0 10 20 30 40 50 60
0 2 4 6 8 10 12
Musical Note

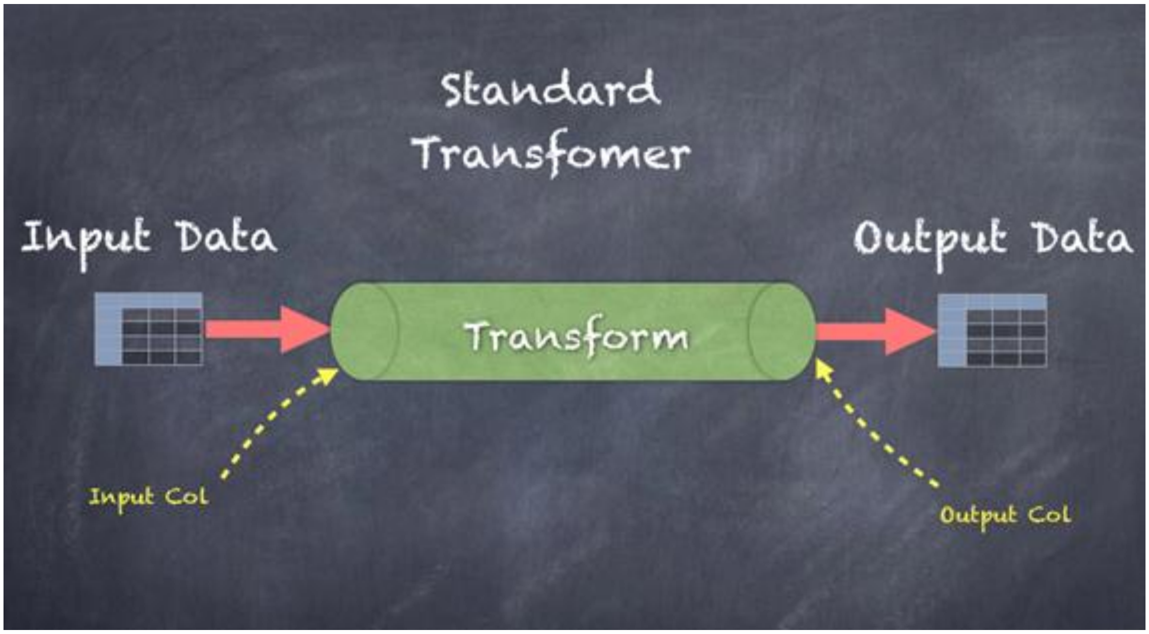

Visualization of Sound Spectrum
0
2
4
6
8
10
0
5
10
15
20
Histogram of Notes
Count
60
50
40
30
20
10
0
0
1
2
3
4
5
6
7
8
Musical Note

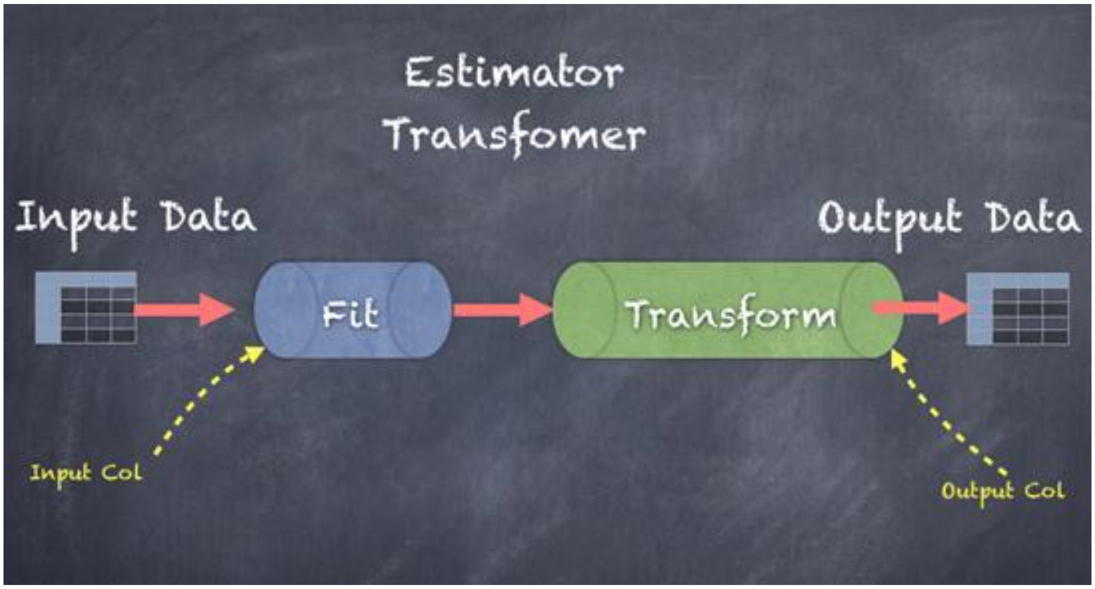

Visualization of Sound Spectrum
0
2
4
6
8
10
0
10
20
30
40
Histogram of Notes
Count
60
50
40
30
20
10
0
0
2
4
6
8
10
Musical Note


predicted vs actual values
Prediction
Actual
count
12
10
8
6
4
2
0
10
20
30
40
50
Median house price in $1,000s

Chapter 06: Predictive Analytics Pipelines for NLP







Estimator

Transfomer

Input Data

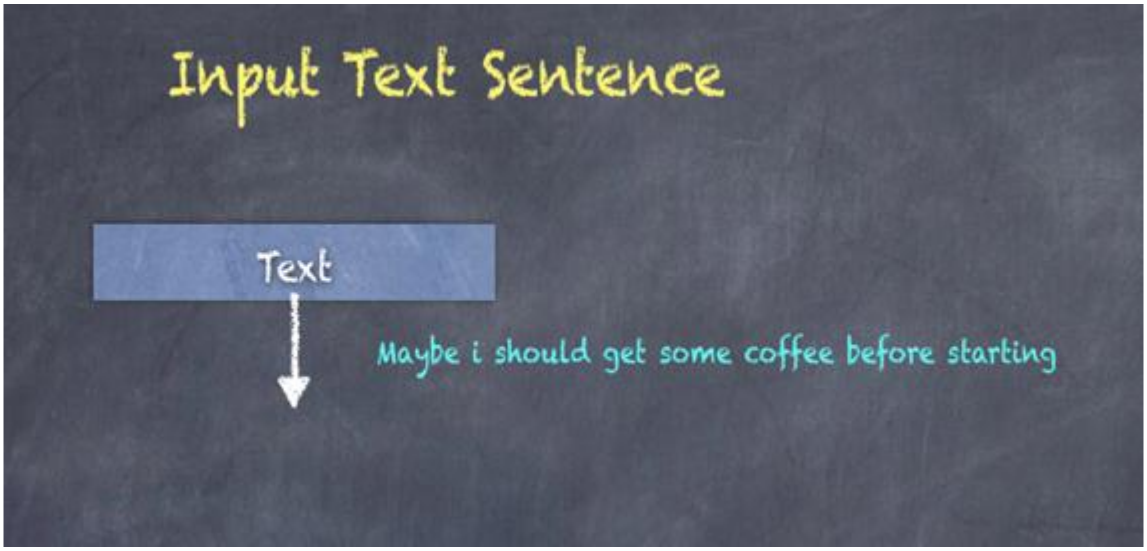
Fit

Transform

Output Data

Input Col

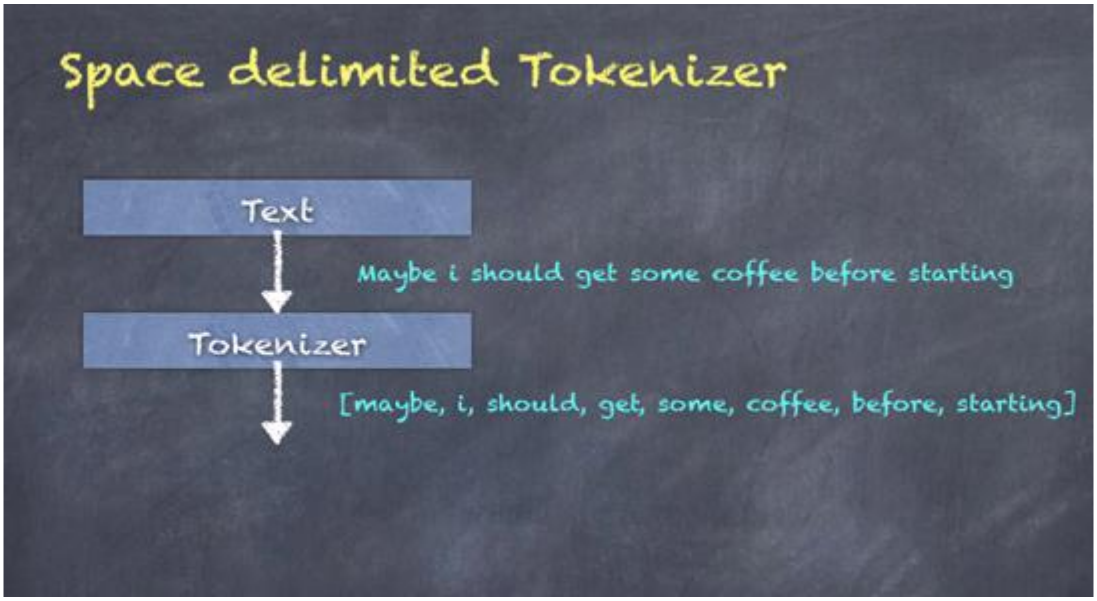
Output Col



Input Text Sentence

Text

Maybe i should get some coffee before starting



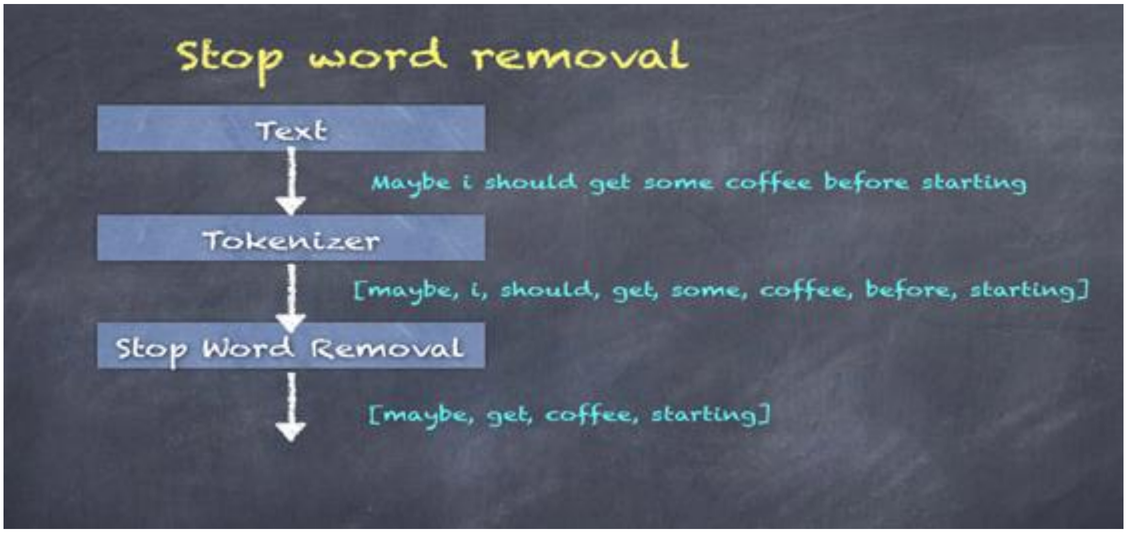
Space delimited Tokenizer

Text

Maybe i should get some coffee before starting

Tokenizer

[maybe, i, should, get, some, coffee, before, starting]



Stop word removal

Text

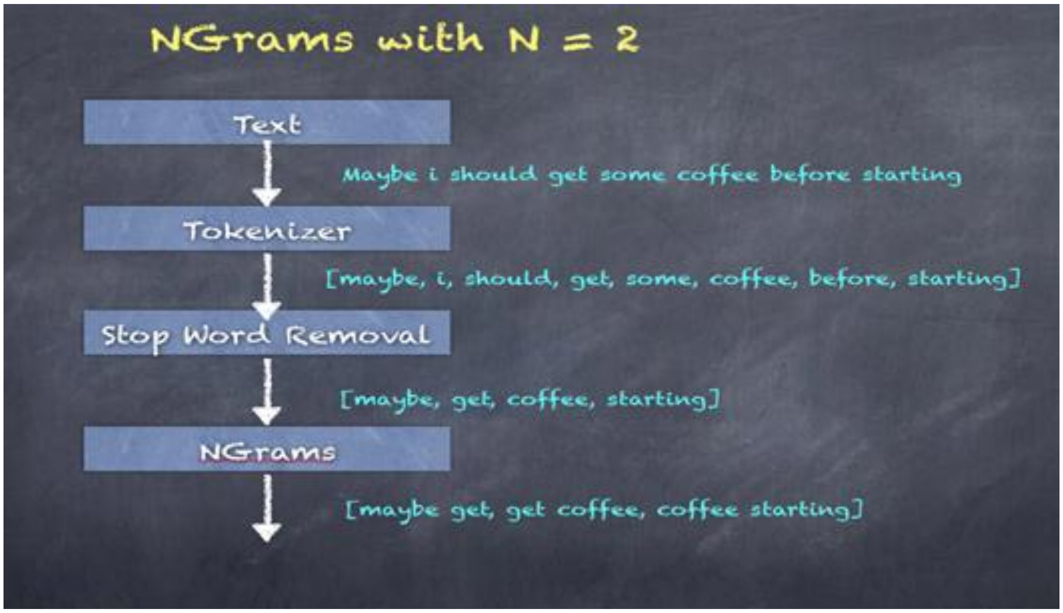
Maybe i should get some coffee before starting

Tokenizer

[maybe, i, should, get, some, coffee, before, starting]

Stop Word Removal

[maybe, get, coffee, starting]



NGrams with N = 2

Text

Maybe i should get some coffee before starting

Tokenizer

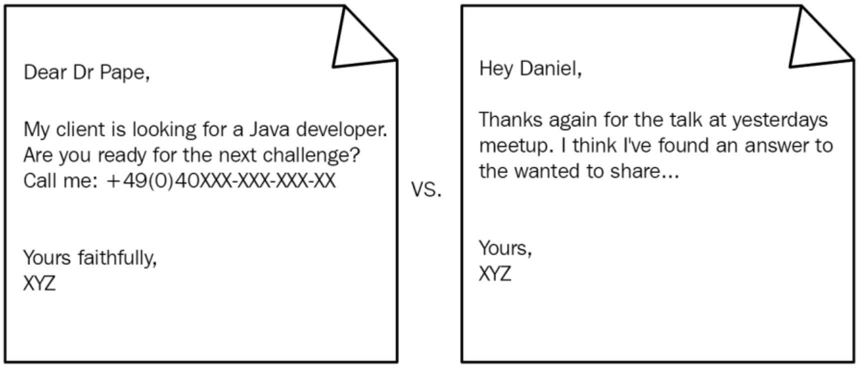
[maybe, i, should, get, some, coffee, before, starting]

Stop Word Removal

[maybe, get, coffee, starting]

NGrams

[maybe get, get coffee, coffee starting]



Dear Dr Pape,

My client is looking for a Java developer. Are you ready for the next challenge? Call me: +49(0)40XXX-XXX-XXX-XX

Yours faithfully,
XYZ

VS.

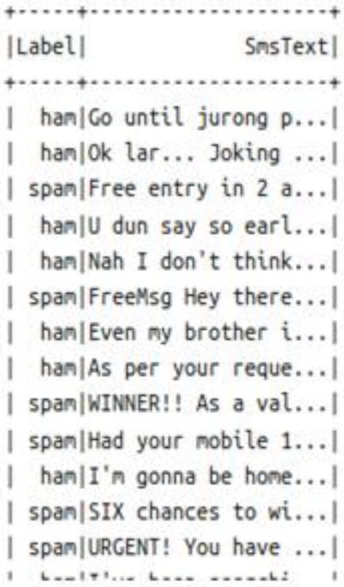
Hey Daniel,

Thanks again for the talk at yesterdays meetup. I think I've found an answer to the wanted to share...

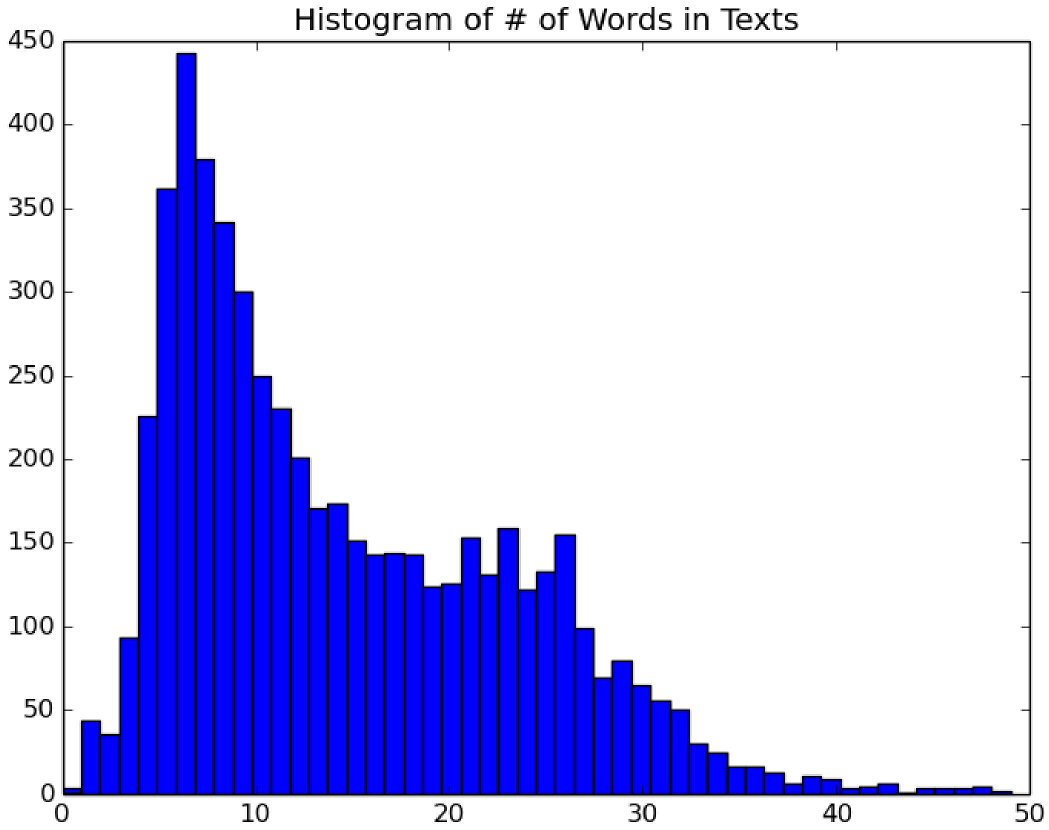
Yours,
XYZ

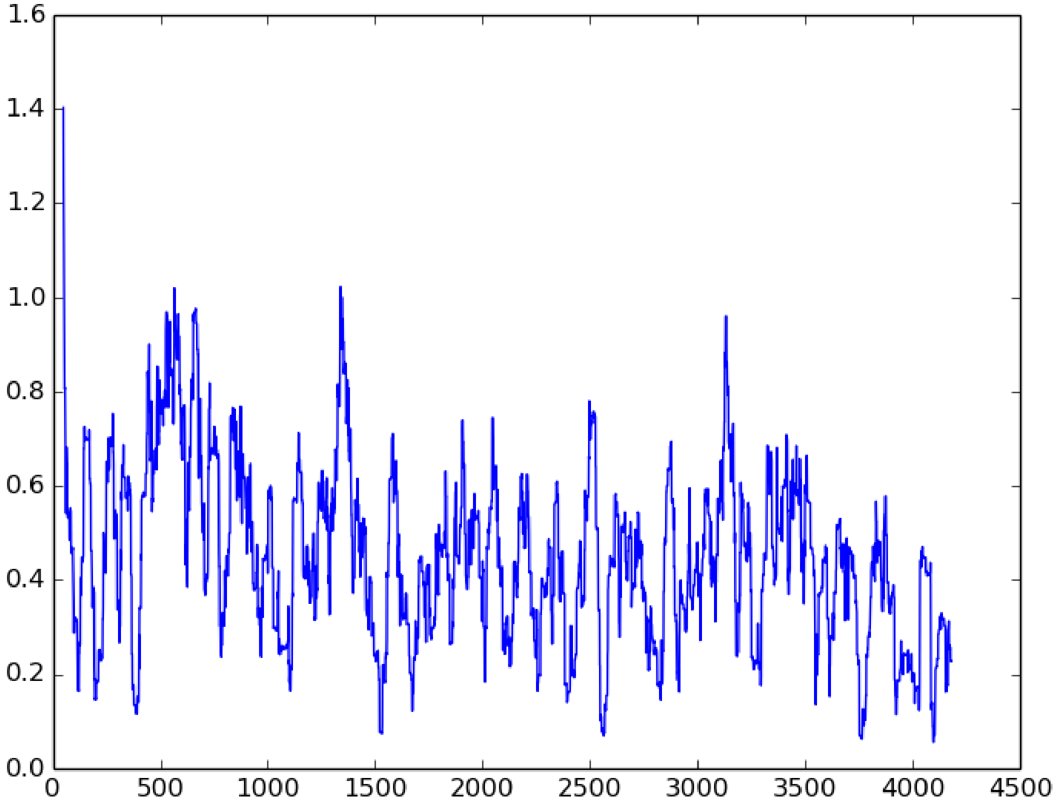
SPAM

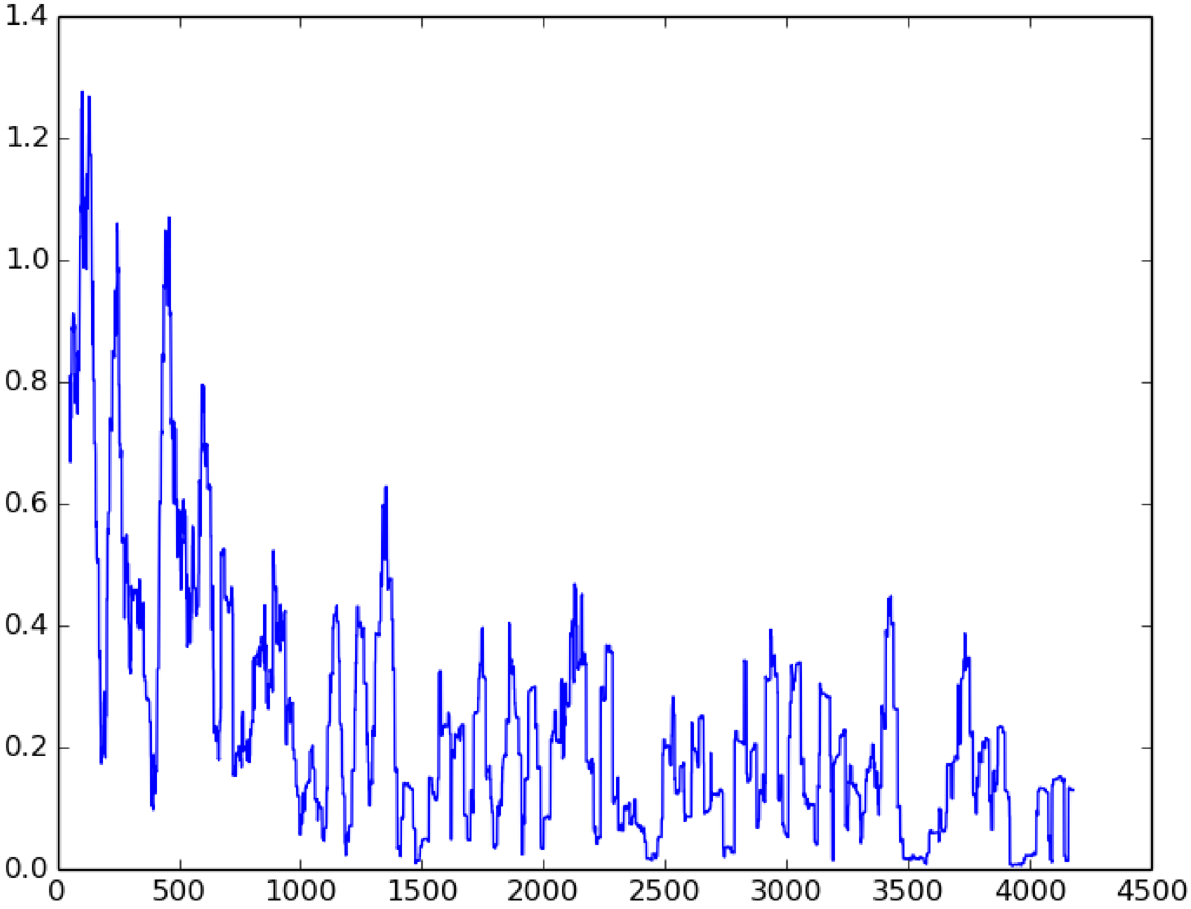
HAM

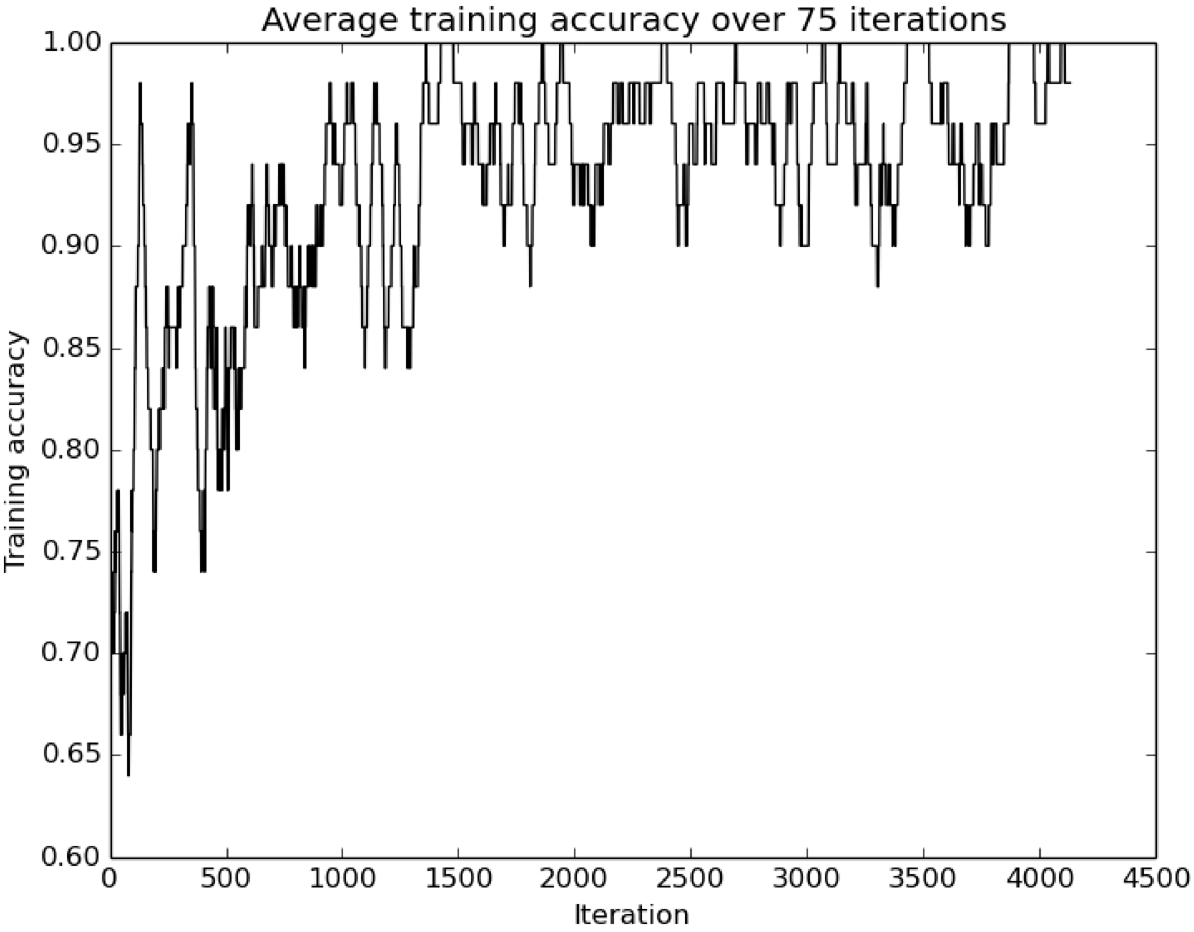


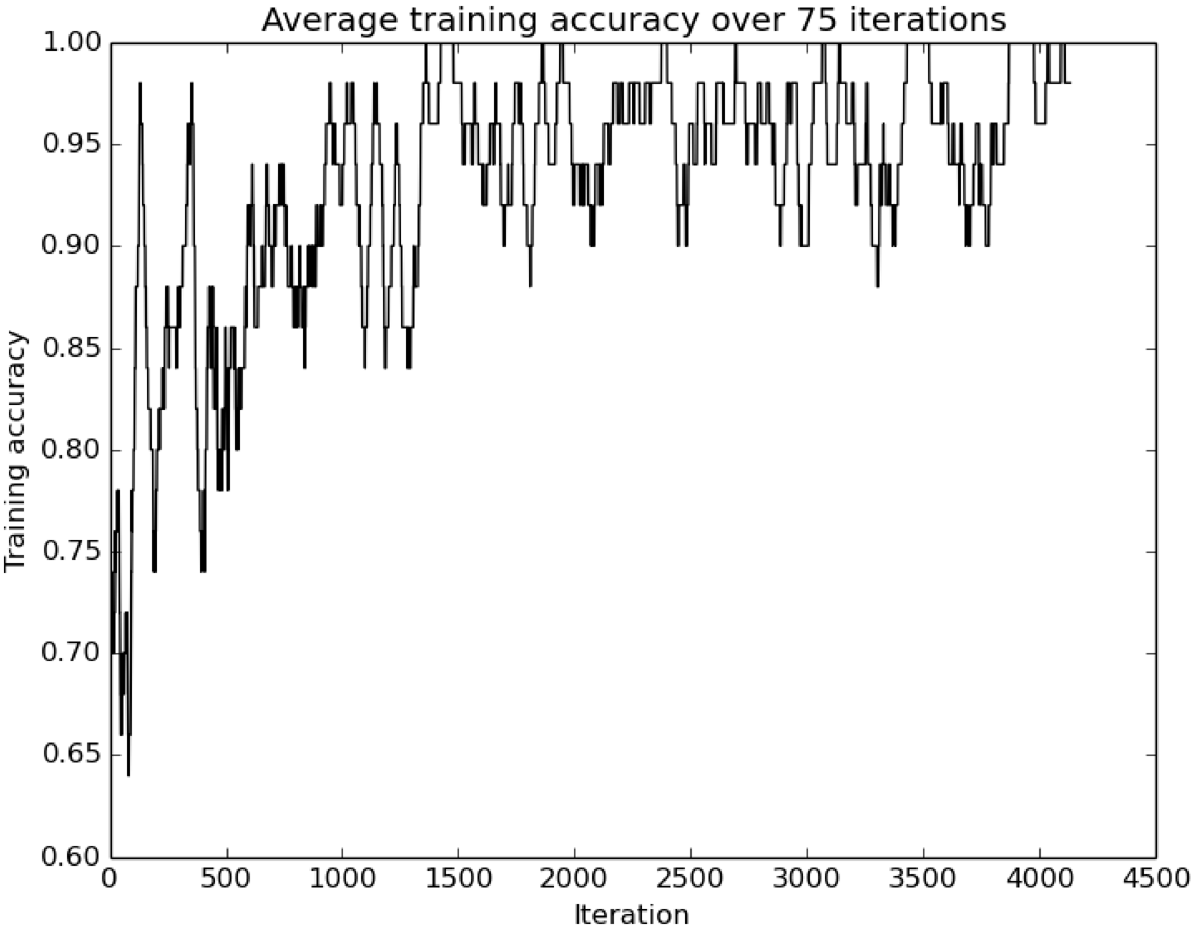
```
+-----+--------------------+
|Label|             SmsText|
+-----+--------------------+
|  ham|Go until jurong p...|
|  ham|Ok lar... Joking ...|
| spam|Free entry in 2 a...|
|  ham|U dun say so earl...|
|  ham|Nah I don't think...|
| spam|FreeMsg Hey there...|
|  ham|Even my brother i...|
|  ham|As per your reque...|
| spam|WINNER!! As a val...|
| spam|Had your mobile 1...|
|  ham|I'm gonna be home...|
| spam|SIX chances to wi...|
| spam|URGENT! You have ...|
|  ham|I've been searchi    |
```

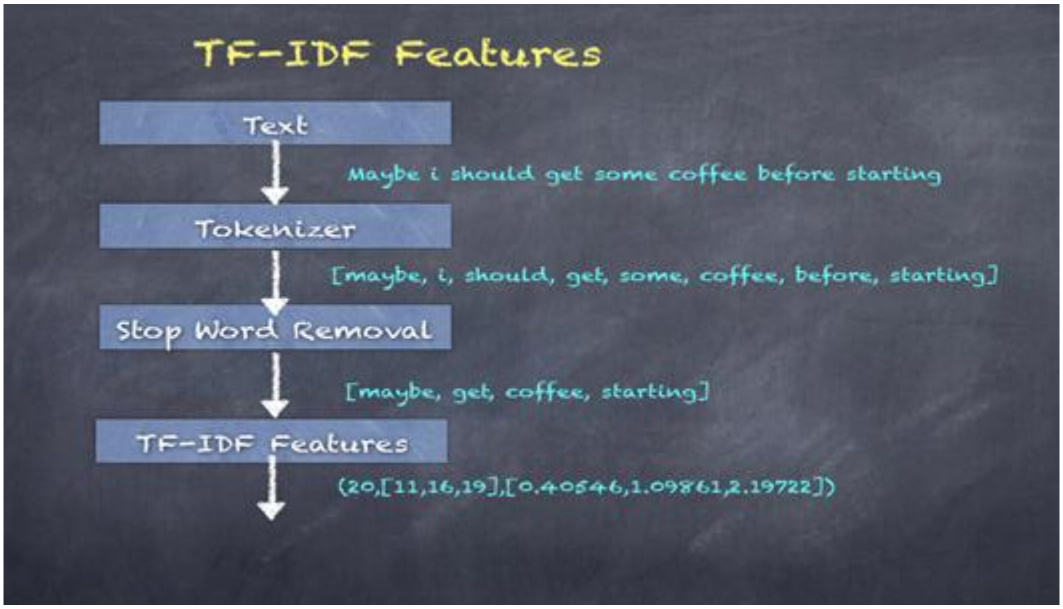

Histogram of # of Words in Texts
450
400
350
300
250
200
150
100
50
0
0
10
20
30
40
50


1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
0
500
1000
1500
2000
2500
3000
3500
4000
4500


1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
0
500
1000
1500
2000
2500
3000
3500
4000
4500


Average training accuracy over 75 iterations
Training accuracy
1.00
0.95
0.90
0.85
0.80
0.75
0.70
0.65
0.60
0
500
1000
1500
2000
2500
3000
3500
4000
4500
Iteration


Average training accuracy over 75 iterations
Training accuracy
1.00
0.95
0.90
0.85
0.80
0.75
0.70
0.65
0.60
Iteration
0
500
1000
1500
2000
2500
3000
3500
4000
4500



TF-IDF Features

Text

Maybe i should get some coffee before starting

Tokenizer

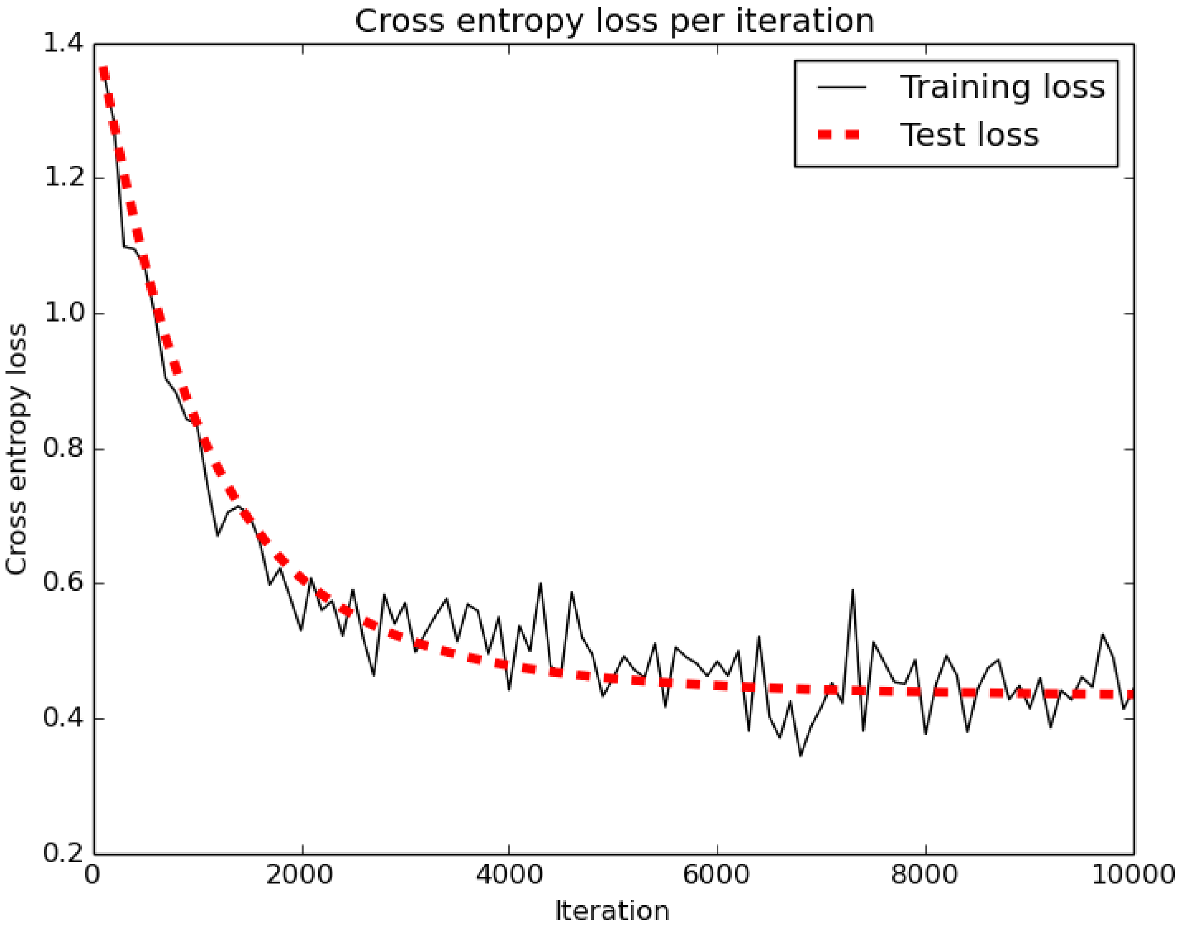
[maybe, i, should, get, some, coffee, before, starting]

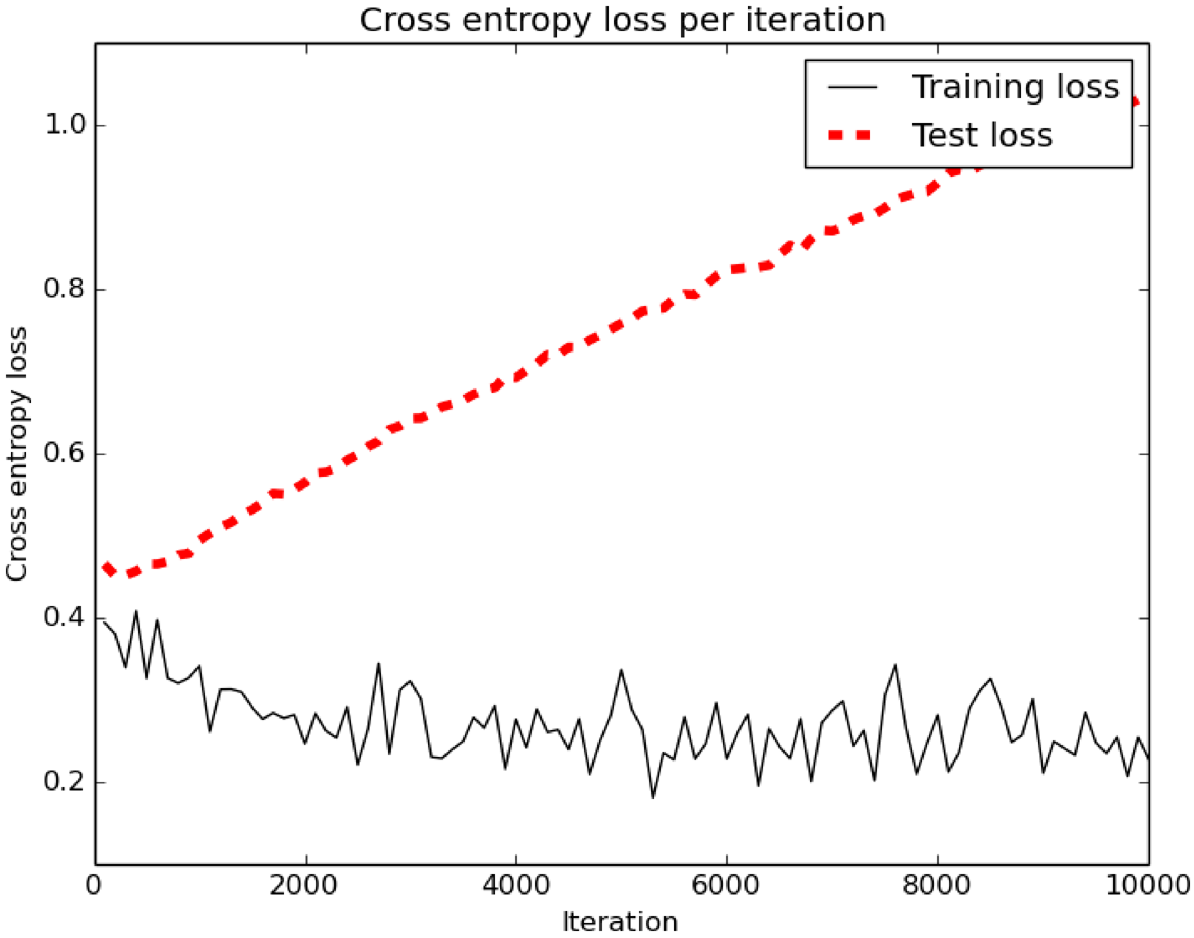
Stop Word Removal

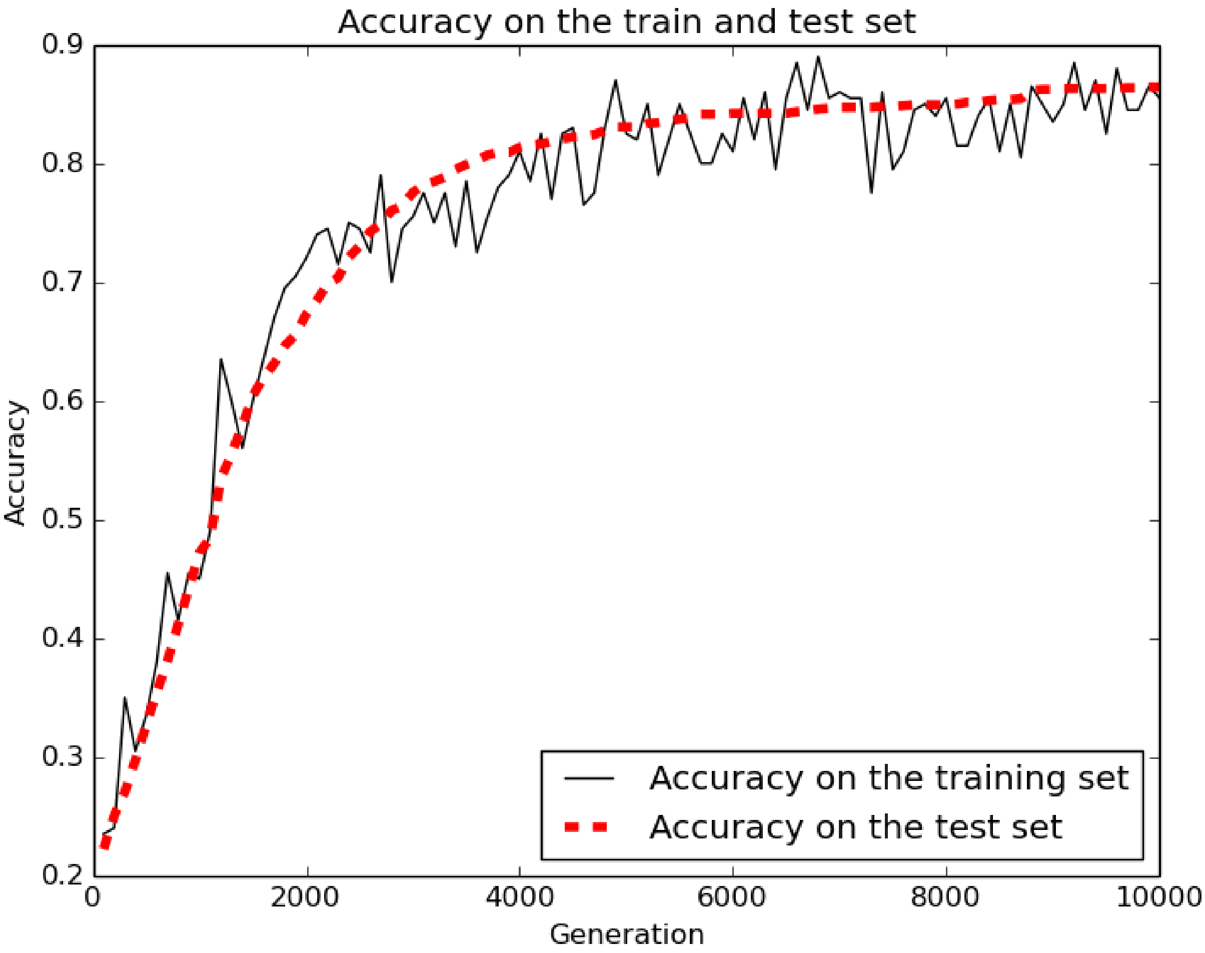
[maybe, get, coffee, starting]

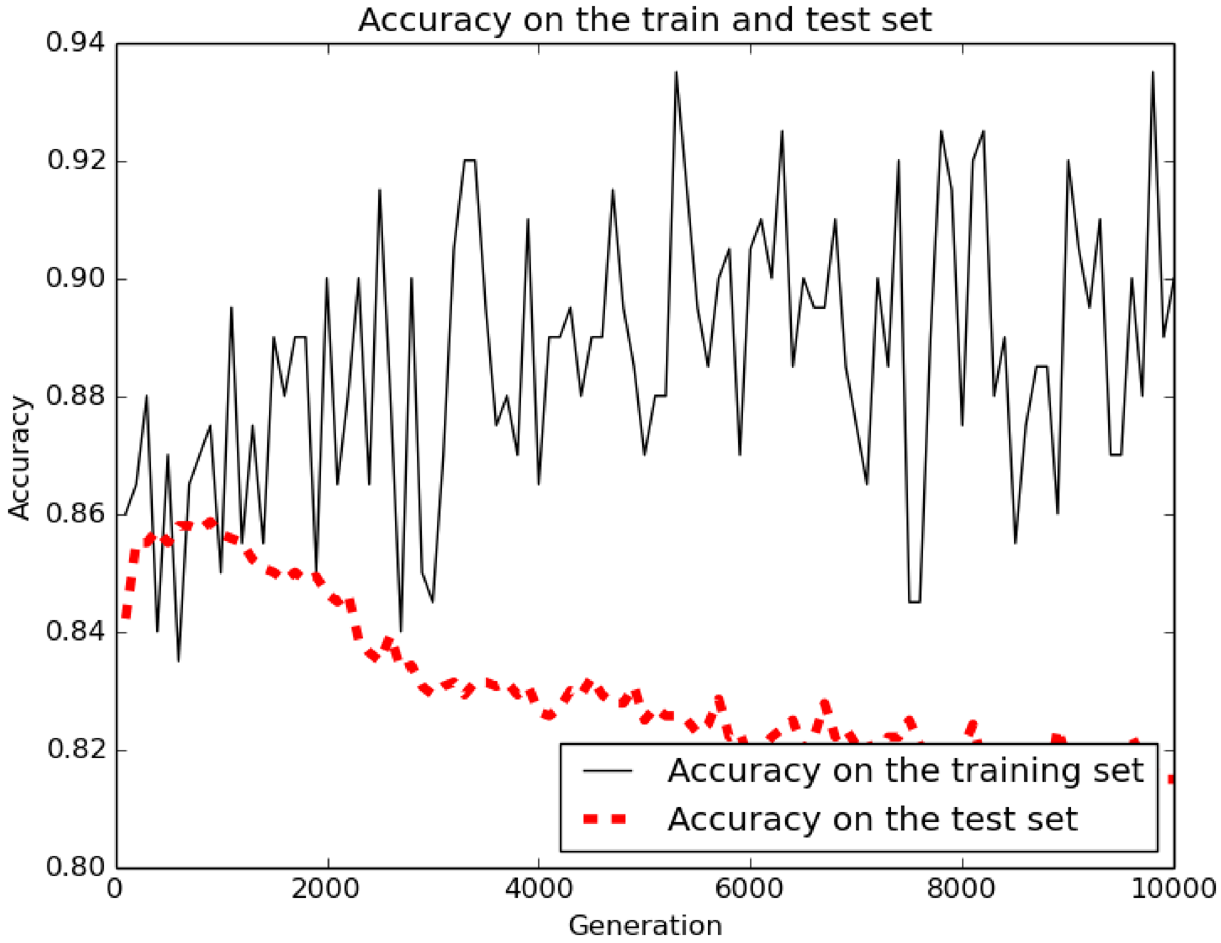
TF-IDF Features

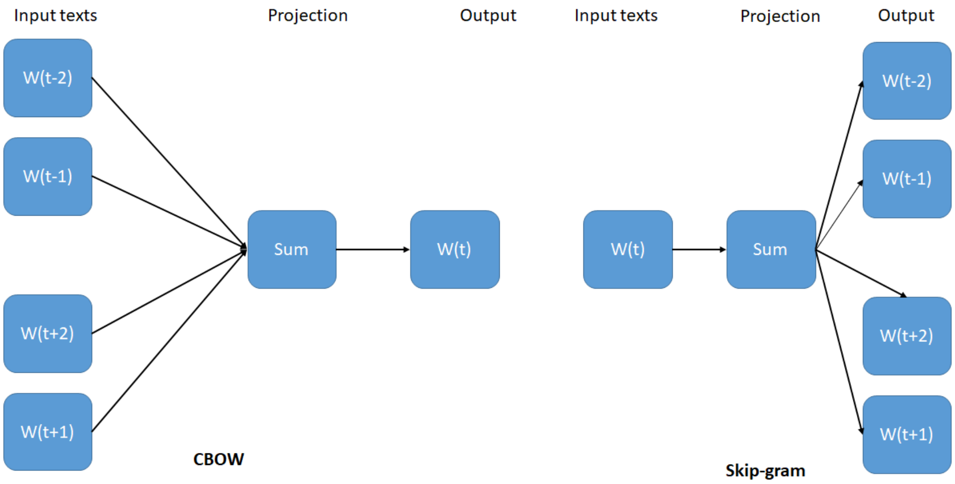
(20,[11,16,19],[0.40546,1.09861,2.19722])

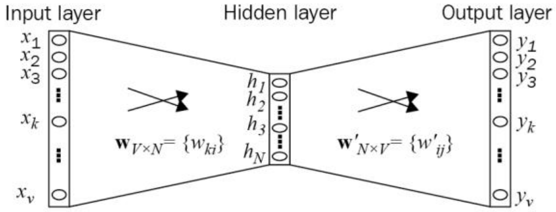

Cross entropy loss per iteration
Cross entropy loss
Iteration
Training loss
Test loss
0.2
0.4
0.6
0.8
1.0
1.2
1.4
0
2000
4000
6000
8000
10000


Cross entropy loss per iteration
Training loss
Test loss
Cross entropy loss
1.0
0.8
0.6
0.4
0.2
0
2000
4000
6000
8000
10000
Iteration

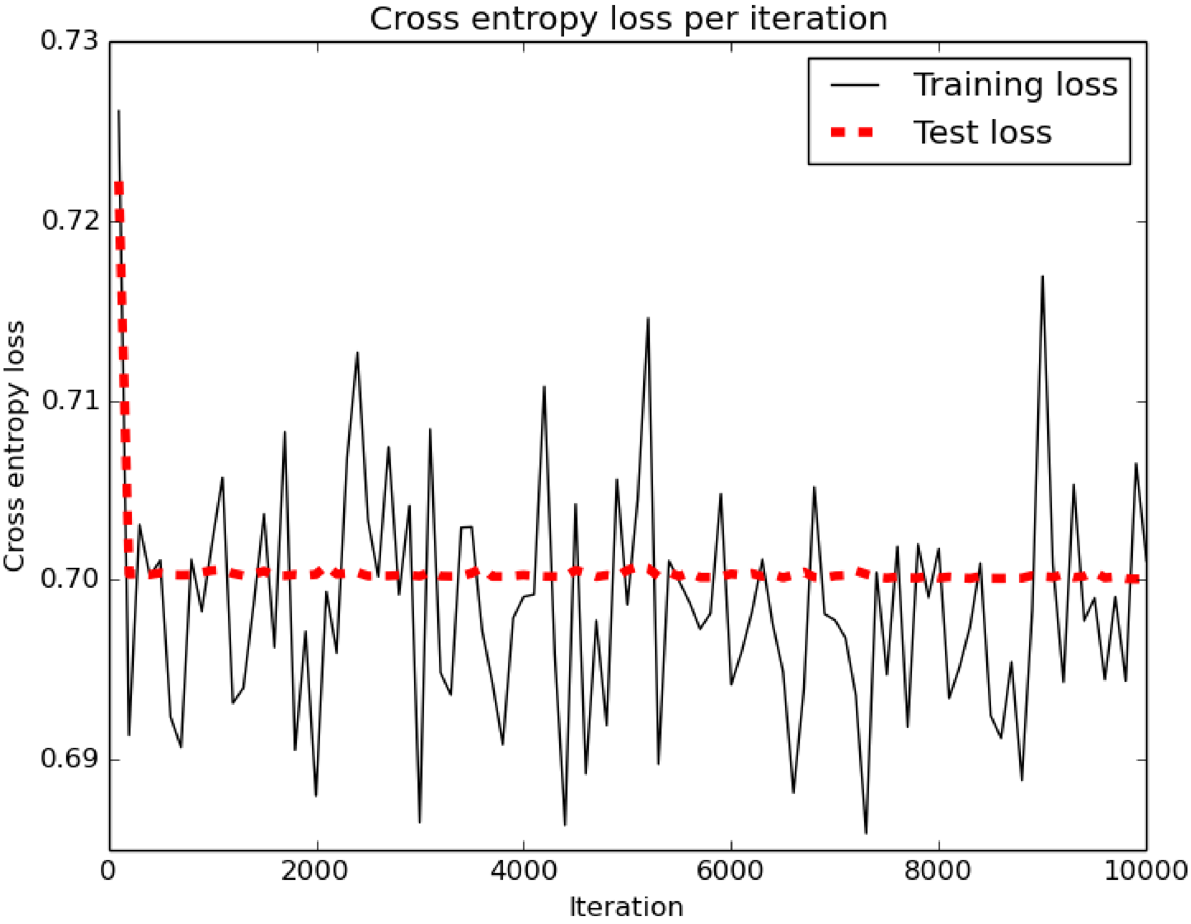

Accuracy on the train and test set
Accuracy
Generation
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0
2000
4000
6000
8000
10000
Accuracy on the training set
Accuracy on the test set

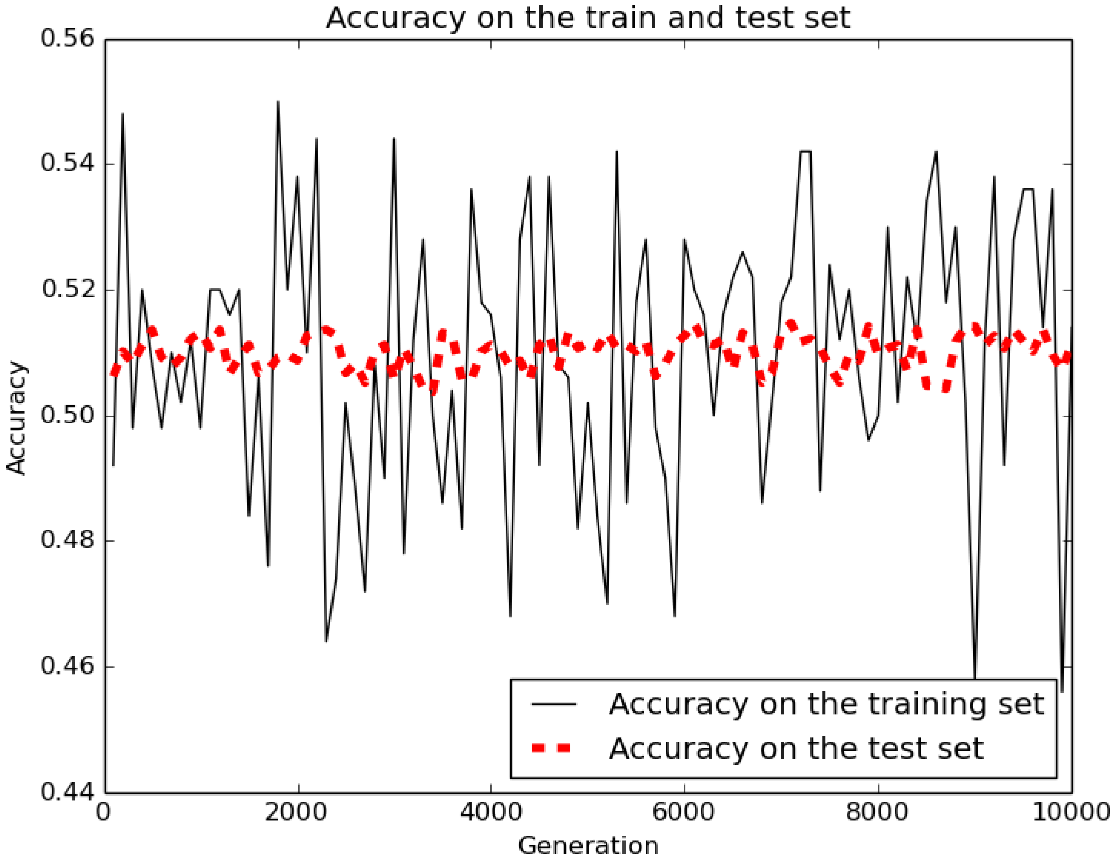

Accuracy on the train and test set
Accuracy
Generation
0.94
0.92
0.90
0.88
0.86
0.84
0.82
0.80
0
2000
4000
6000
8000
10000
Accuracy on the training set
Accuracy on the test set



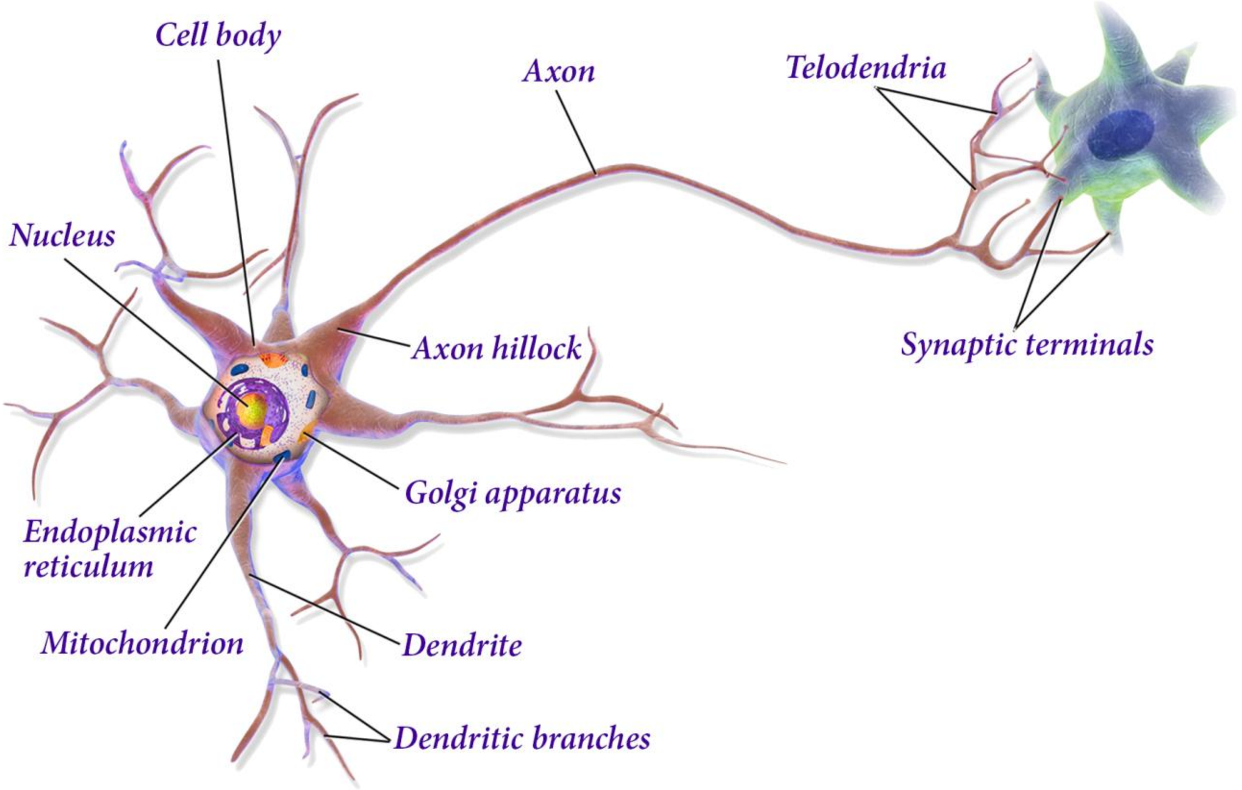


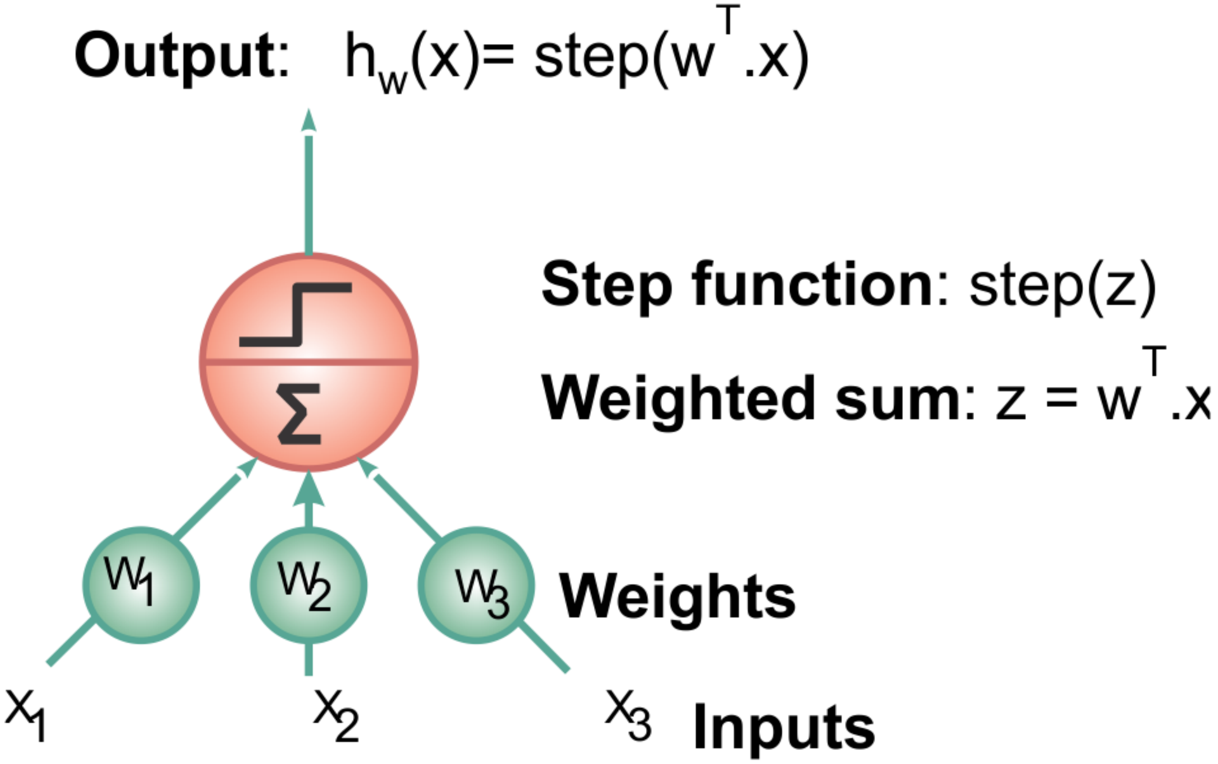
$$\begin{bmatrix} 0 & 0 & 0 & 1 & 0 \end{bmatrix} \times \begin{bmatrix} 17 & 24 & 1 \\ 23 & 5 & 7 \\ 4 & 6 & 13 \\ 10 & 12 & 19 \\ 11 & 18 & 25 \end{bmatrix} = \begin{bmatrix} 10 & 12 & 19 \end{bmatrix}$$

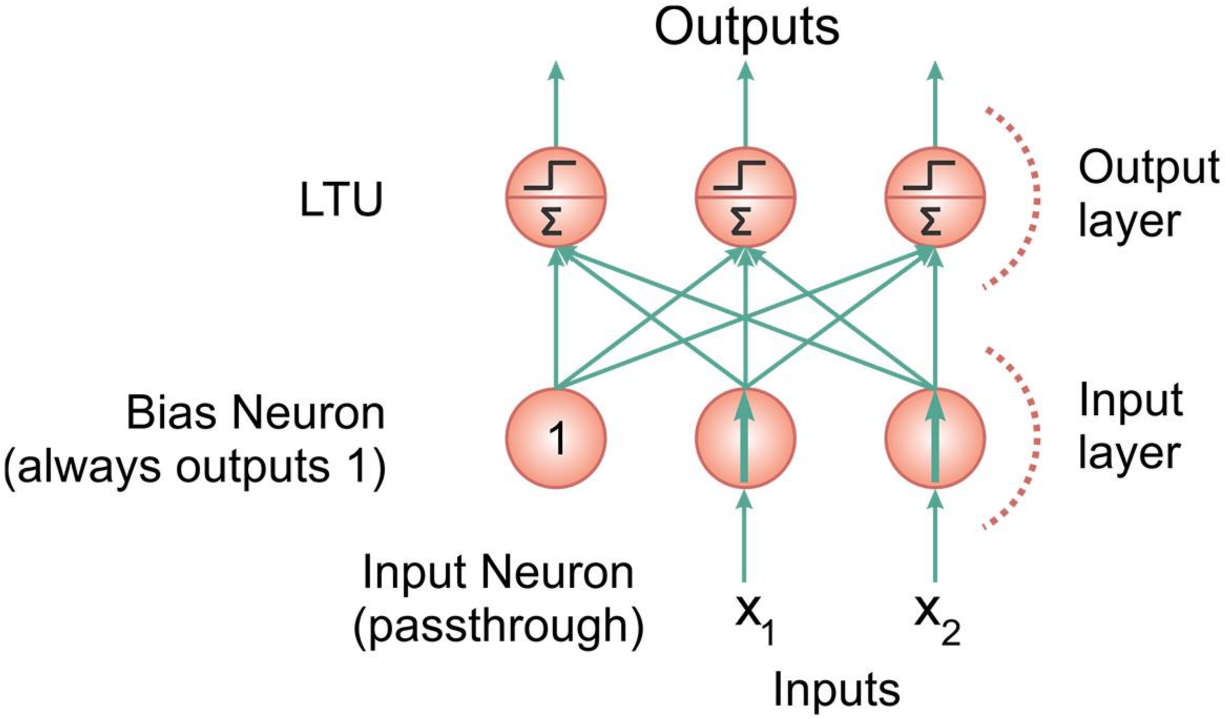

Cross entropy loss per iteration
Training loss
Test loss
Cross entropy loss
0.73
0.72
0.71
0.70
0.69
Iteration
0
2000
4000
6000
8000
10000

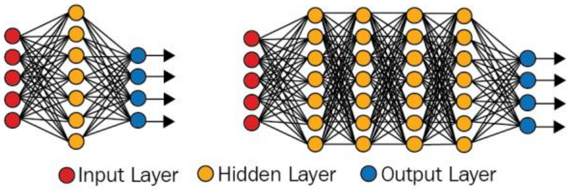

Accuracy on the train and test set
Accuracy
Generation
0.56
0.54
0.52
0.50
0.48
0.46
0.44
0
2000
4000
6000
8000
10000
Accuracy on the training set
Accuracy on the test set

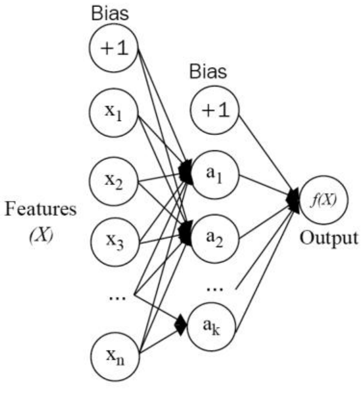
Chapter 07: Using Deep Neural Networks for Predictive Analytics

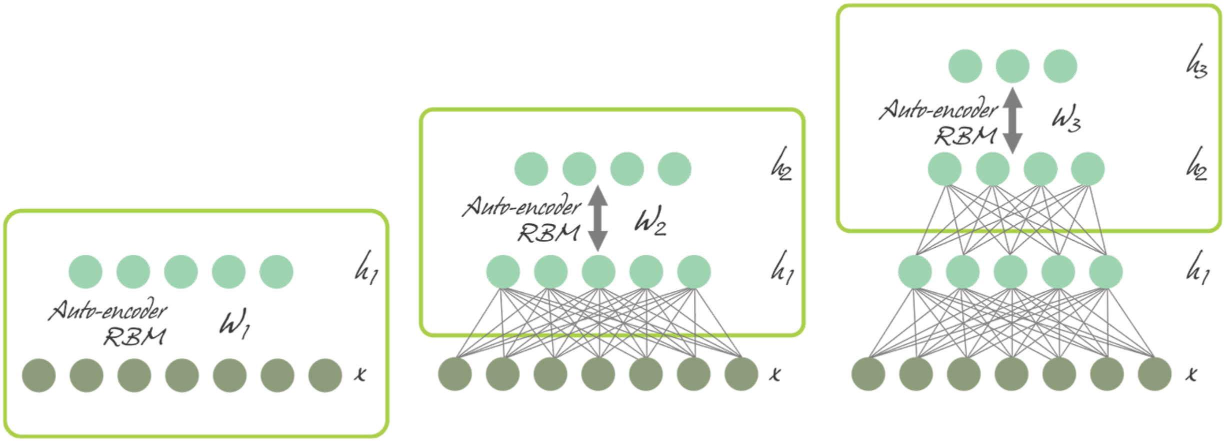


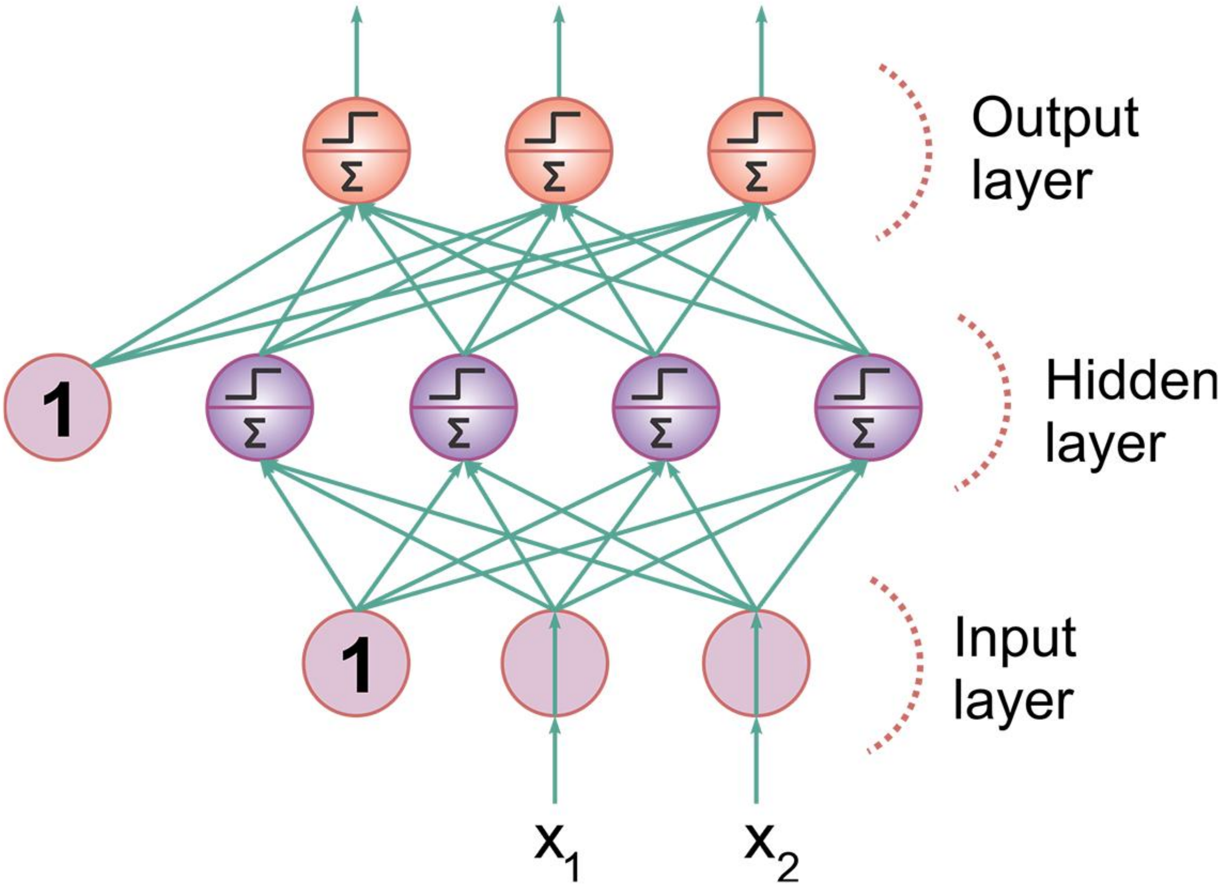

Output: $h_w(x)= step(w^T.x)$
Step function: step(z)
Weighted sum: $z = w^T.x$
Σ
w_1
w_2
w_3
Weights
x_1
x_2
x_3
Inputs

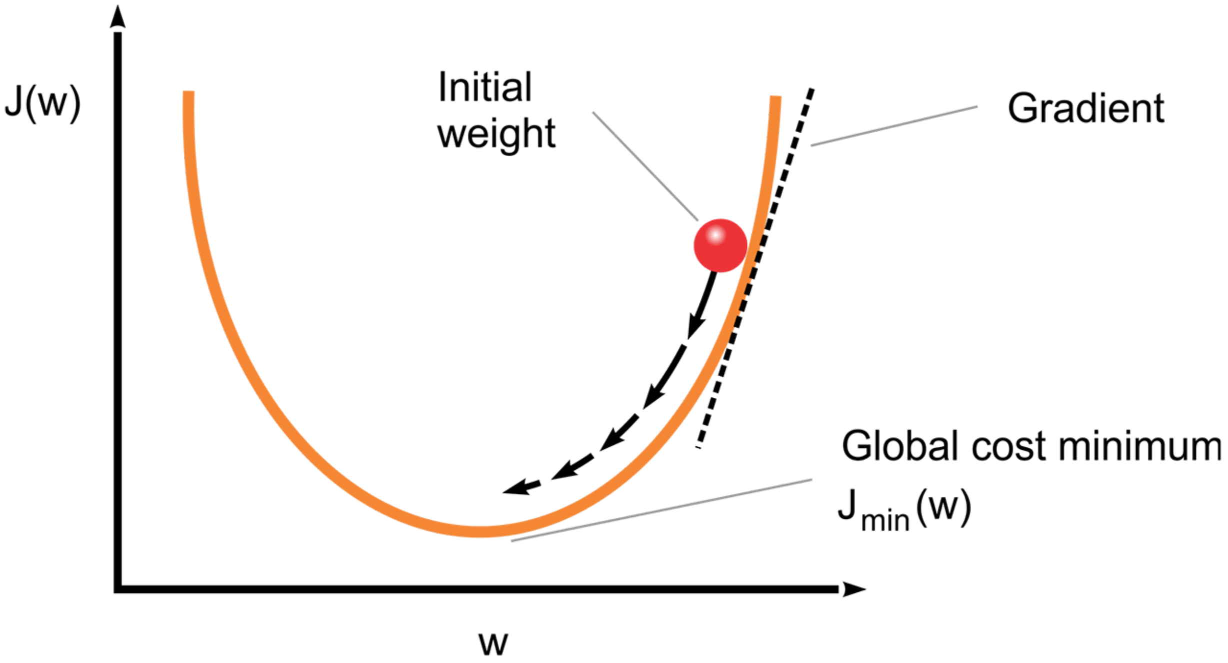

Outputs
LTU
Output layer
Bias Neuron (always outputs 1)
1
Input layer
Input Neuron (passthrough)
x_1
x_2
Inputs

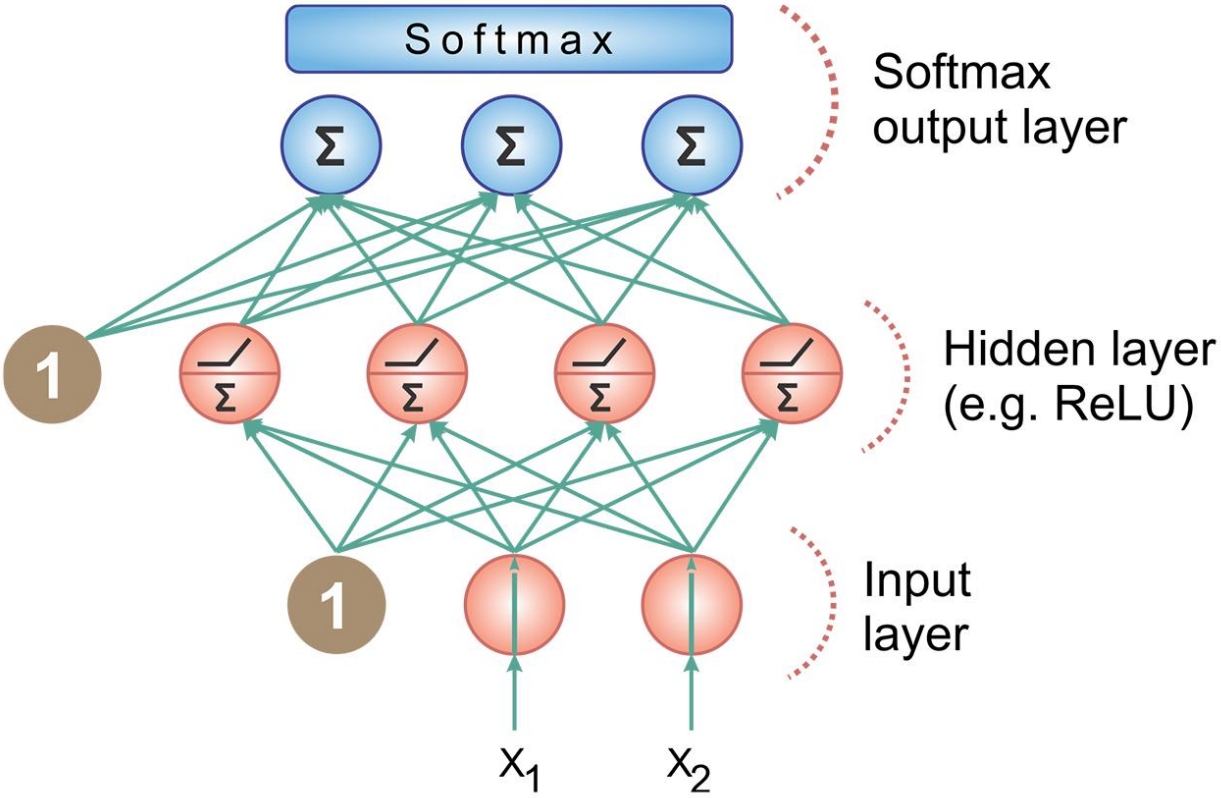

Input Layer
Hidden Layer
Output Layer


Bias
+1
x_1
x_2
x_3
...
x_n
Features
(X)
Bias
+1
a_1
a_2
...
a_k
f(X)
Output


h1
Auto-encoder
RBM
W1
x
h2
Auto-encoder
RBM
W2
h1
x
h3
Auto-encoder
RBM
W3
h2
h1
x


Output layer
Hidden layer
Input layer
1
1
Σ
x_1
x_2


J(w)
Initial weight
Gradient
Global cost minimum
$J_{min}(w)$
w


Softmax
Σ
Σ
Σ
Softmax output layer
1
Σ
Σ
Σ
Σ
Hidden layer (e.g. ReLU)
1
Input layer
x_1
x_2

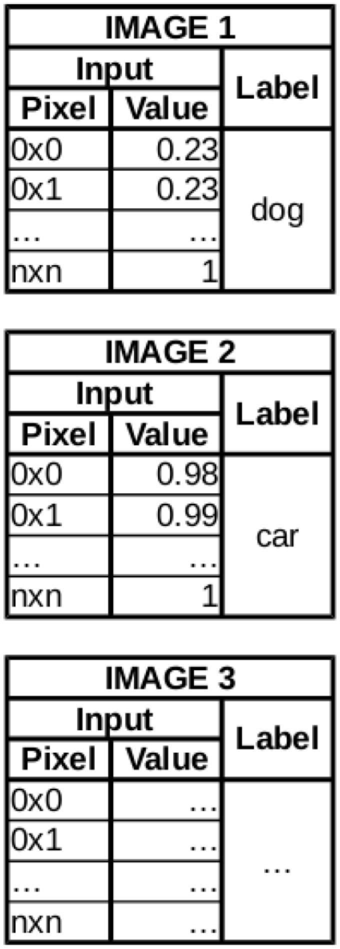


IMAGE 1		
Input		Label
Pixel	Value	
0x0	0.23	dog
0x1	0.23	
…	…	
nxn	1	

IMAGE 2		
Input		Label
Pixel	Value	
0x0	0.98	car
0x1	0.99	
…	…	
nxn	1	

IMAGE 3		
Input		Label
Pixel	Value	
0x0	…	…
0x1	…	
…	…	
nxn	…	

(a)

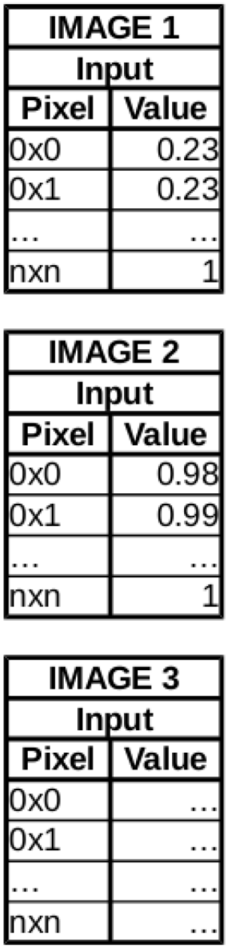
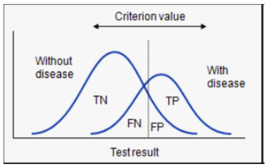


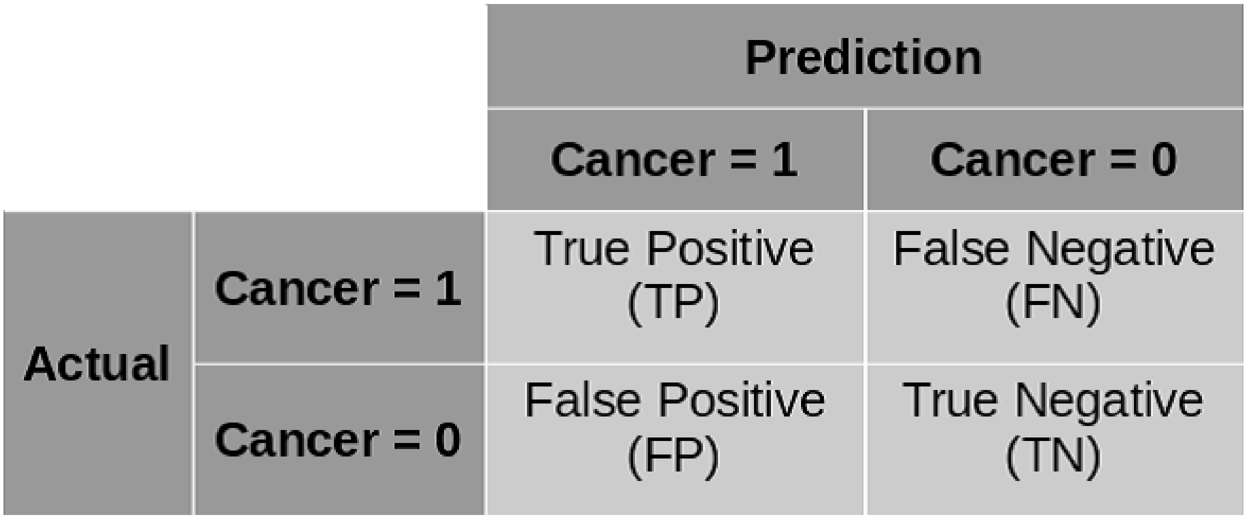
IMAGE 1	
Input	
Pixel	Value
0x0	0.23
0x1	0.23
…	…
nxn	1

IMAGE 2	
Input	
Pixel	Value
0x0	0.98
0x1	0.99
…	…
nxn	1

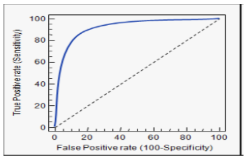
IMAGE 3	
Input	
Pixel	Value
0x0	…
0x1	…
…	…
nxn	…

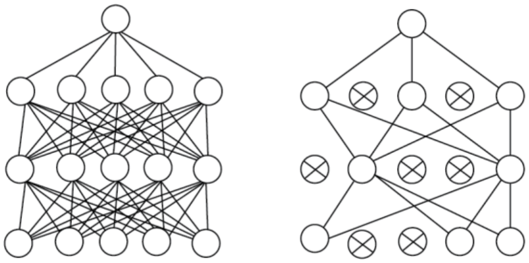
(b)





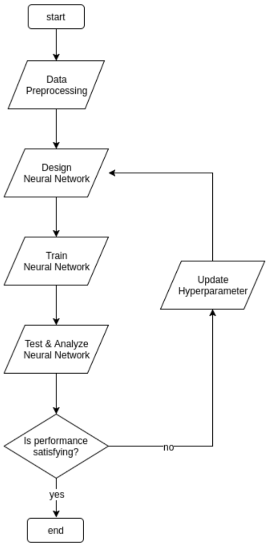
		Prediction	
		Cancer = 1	Cancer = 0
Actual	Cancer = 1	True Positive (TP)	False Negative (FN)
	Cancer = 0	False Positive (FP)	True Negative (TN)

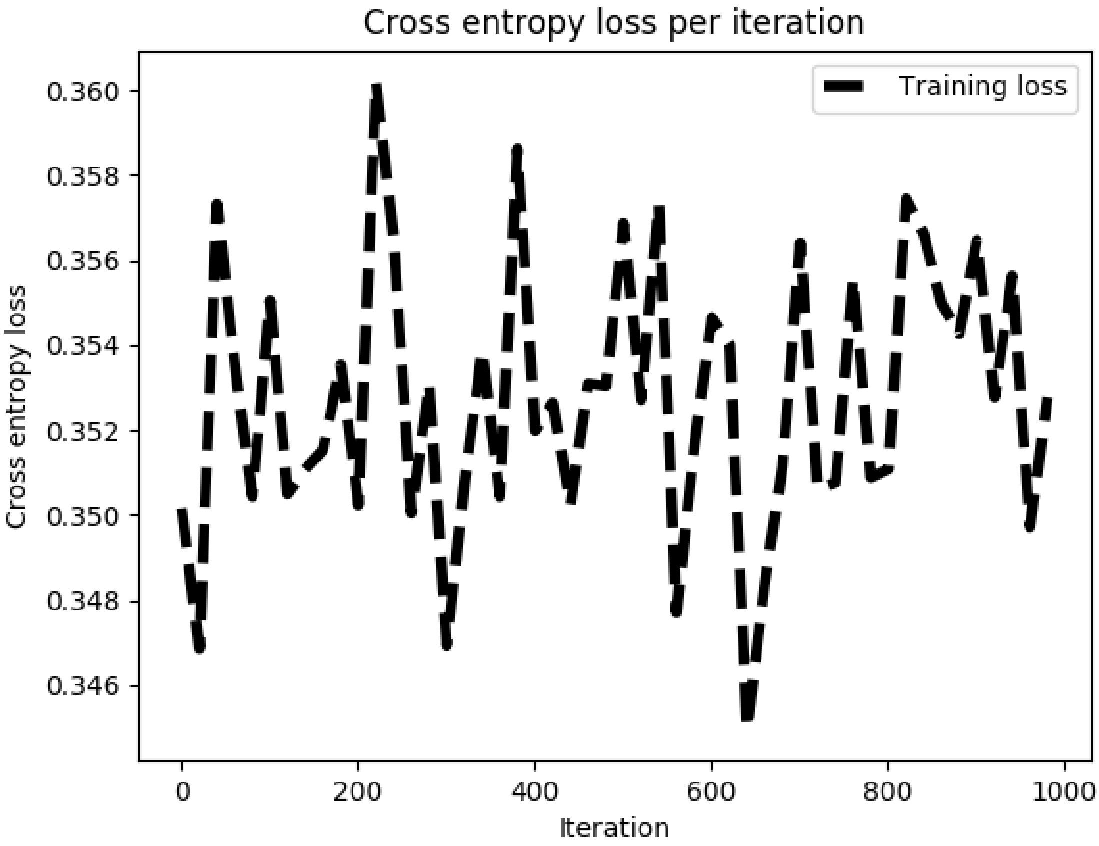


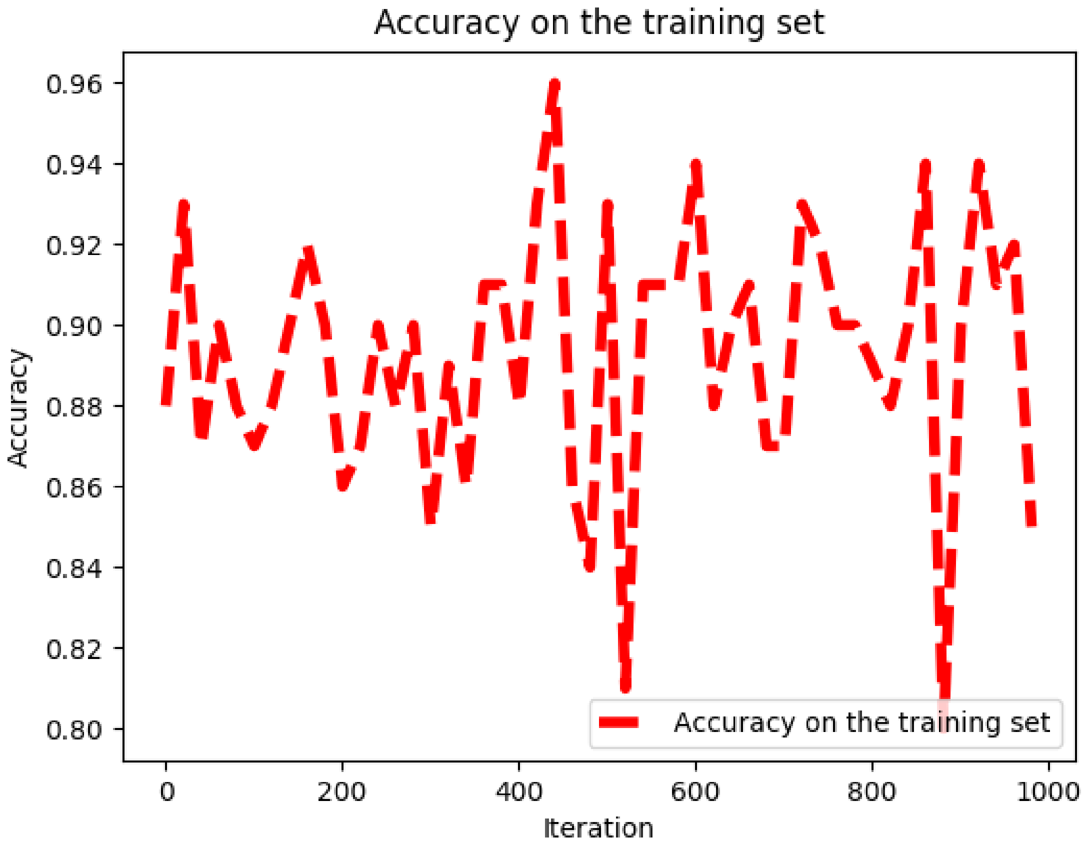


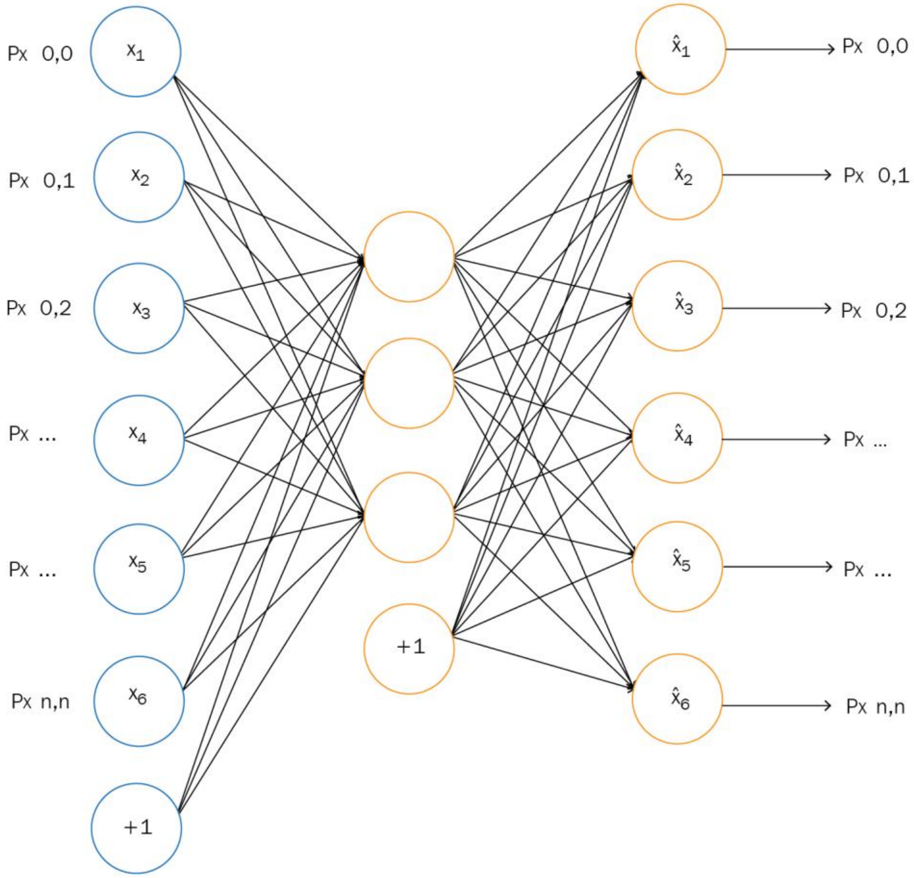
(a)stander Neural Net

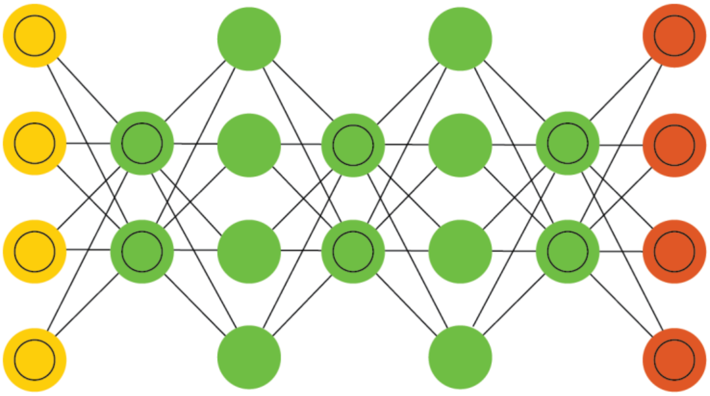
(b) After applying dropout

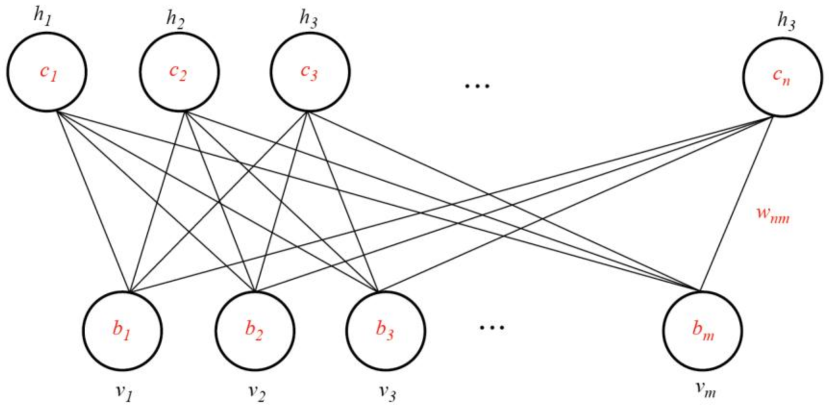

start
Data Preprocessing
Design Neural Network
Train Neural Network
Test & Analyze Neural Network
Is performance satisfying?
no
Update Hyperparameter
yes
end

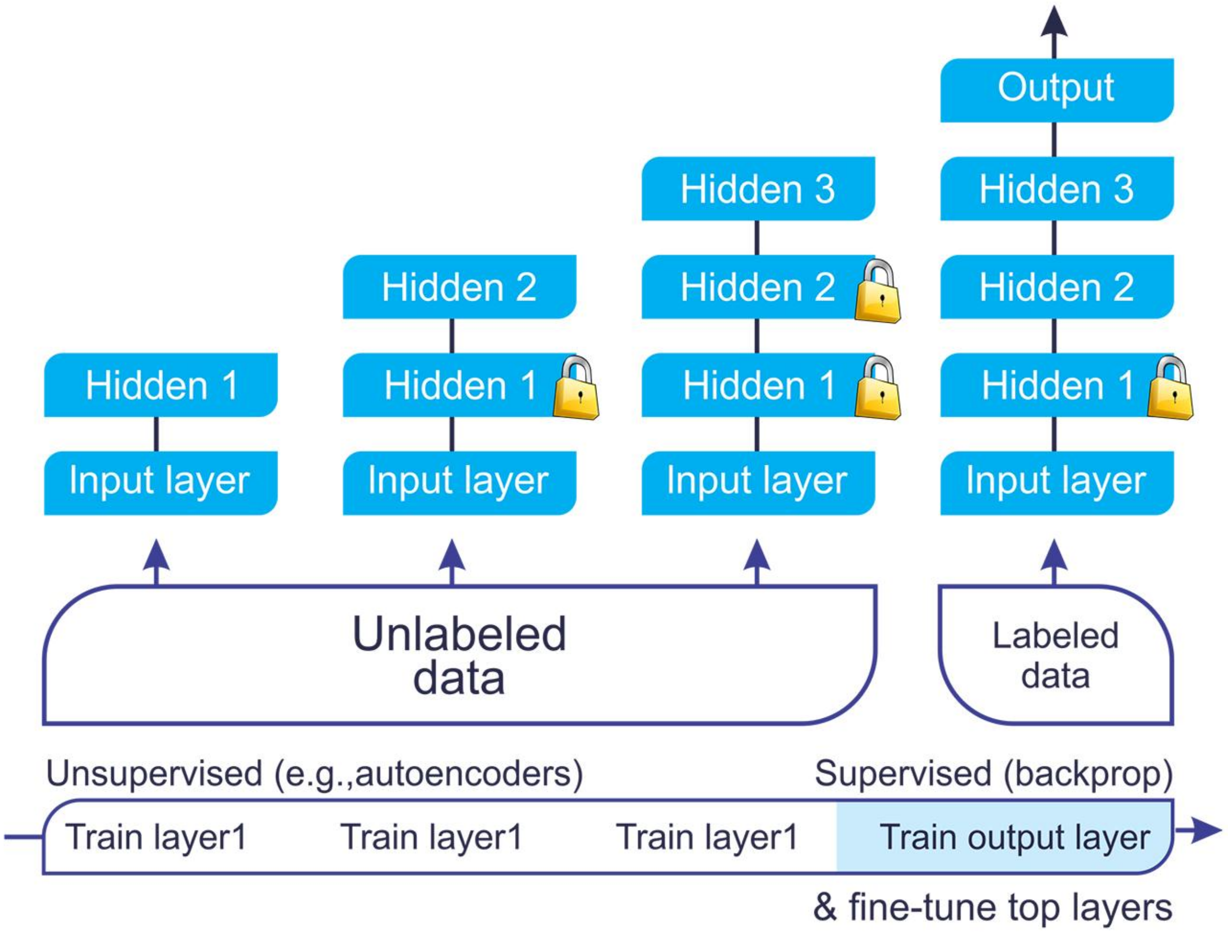

Cross entropy loss per iteration
Training loss
Cross entropy loss
0.360
0.358
0.356
0.354
0.352
0.350
0.348
0.346
Iteration
0
200
400
600
800
1000

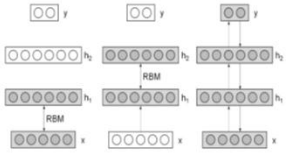

Accuracy on the training set
Accuracy
0.80
0.82
0.84
0.86
0.88
0.90
0.92
0.94
0.96
Iteration
0
200
400
600
800
1000
Accuracy on the training set

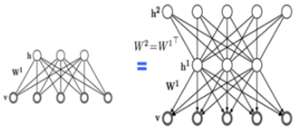

Px 0,0
Px 0,1
Px 0,2
Px ...
Px ...
Px n,n
x_1
x_2
x_3
x_4
x_5
x_6
+1
+1
$\hat{x}_1$
$\hat{x}_2$
$\hat{x}_3$
$\hat{x}_4$
$\hat{x}_5$
$\hat{x}_6$
Px 0,0
Px 0,1
Px 0,2
Px ...
Px ...
Px n,n

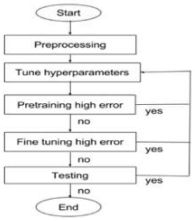


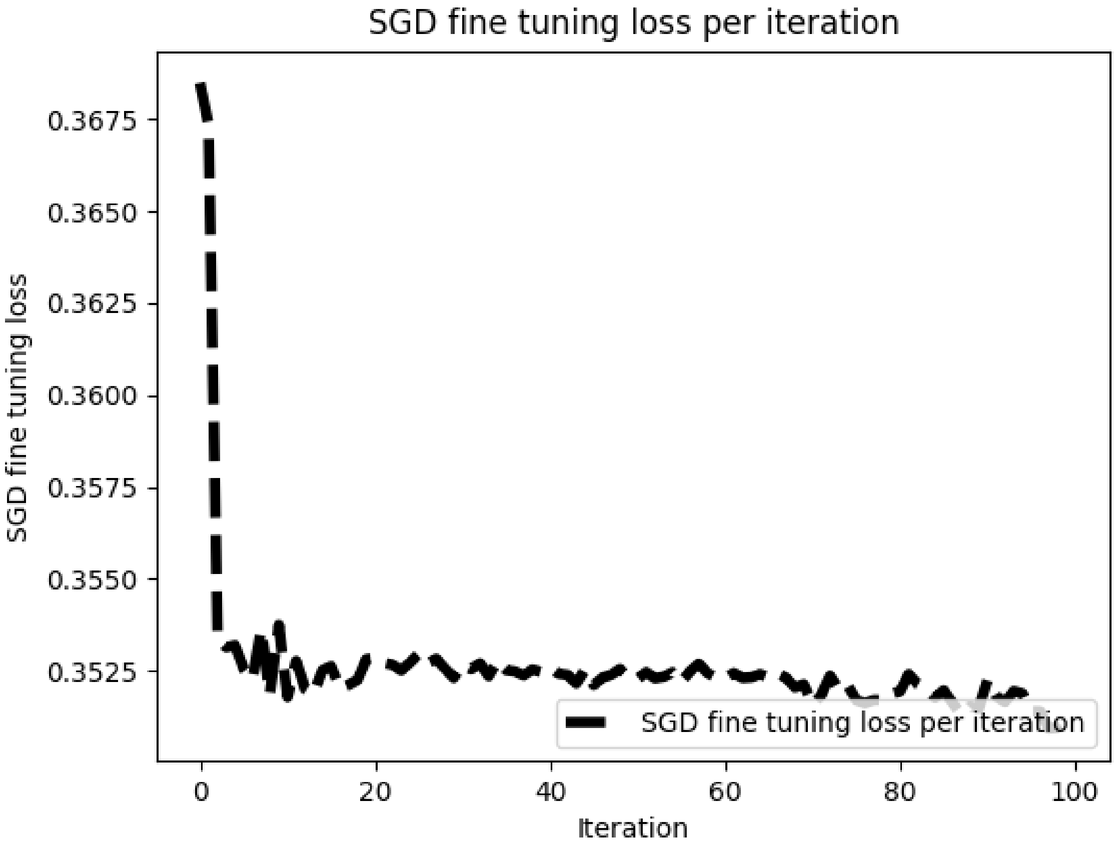

h1
h2
h3
h3
c1
c2
c3
...
cn
wnm
b1
b2
b3
...
bm
v1
v2
v3
vm

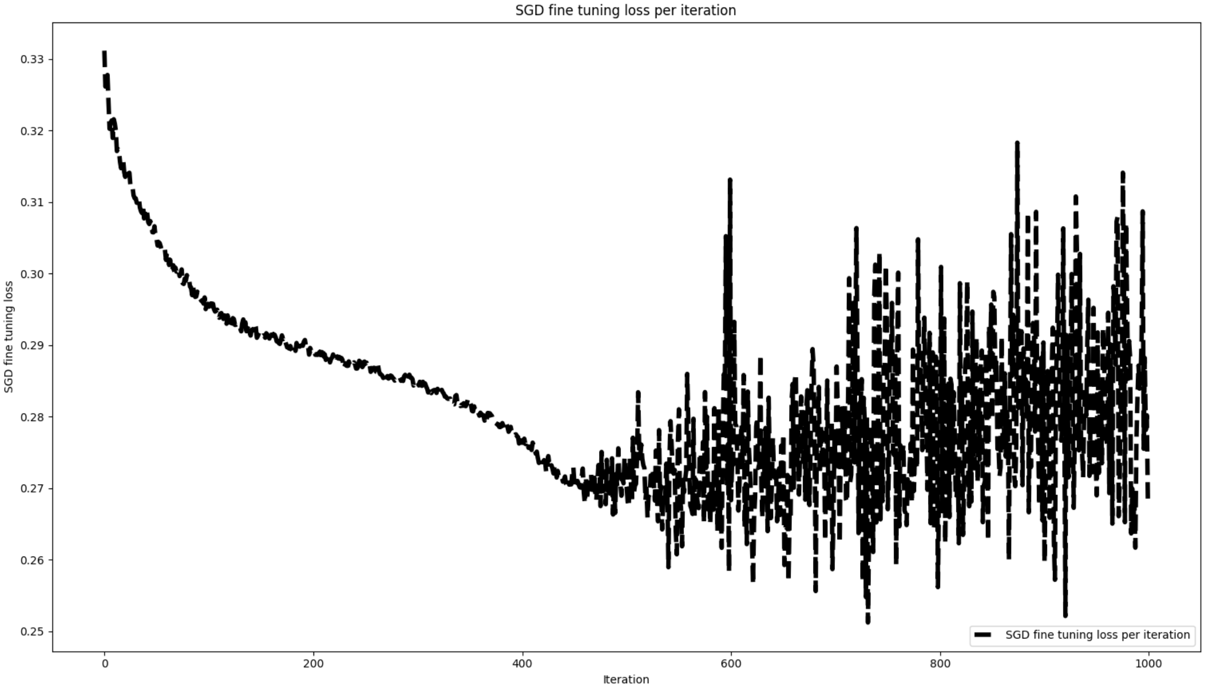

Output
Hidden 3
Hidden 3
Hidden 2
Hidden 2
Hidden 2
Hidden 1
Hidden 1
Hidden 1
Hidden 1
Input layer
Input layer
Input layer
Input layer
Unlabeled data
Labeled data
Unsupervised (e.g.,autoencoders)
Supervised (backprop)
Train layer1
Train layer1
Train layer1
Train output layer
& fine-tune top layers


y
y
y
h2
h2
h2
RBM
h1
h1
h1
RBM
x
x
x

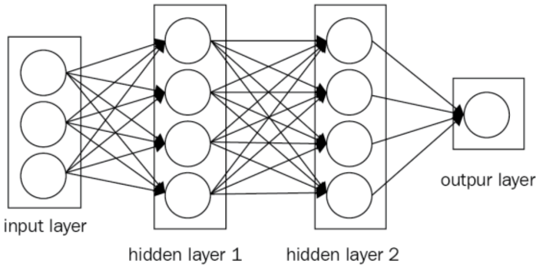

h
W1
v
h2
W2 = W1ᵀ
=
h1
W1
v

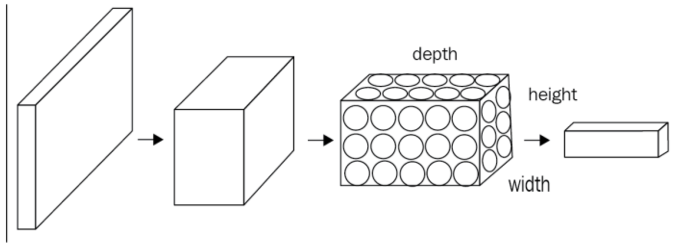

Start
Preprocessing
Tune hyperparameters
Pretraining high error
yes
no
Fine tuning high error
yes
no
Testing
yes
no
End

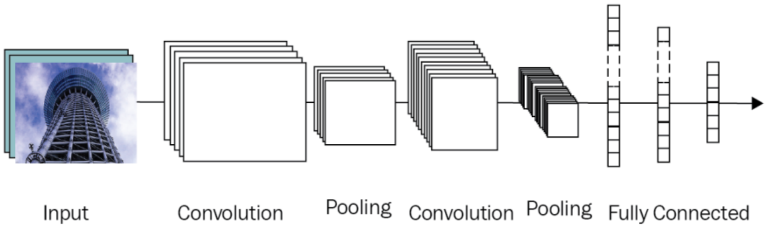

SGD fine tuning loss per iteration
SGD fine tuning loss
0.3675
0.3650
0.3625
0.3600
0.3575
0.3550
0.3525
SGD fine tuning loss per iteration
0
20
40
60
80
100
Iteration

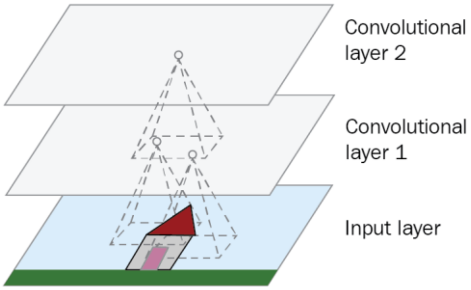

SGD fine tuning loss per iteration
SGD fine tuning loss
0.33
0.32
0.31
0.30
0.29
0.28
0.27
0.26
0.25
Iteration
0
200
400
600
800
1000
SGD fine tuning loss per iteration

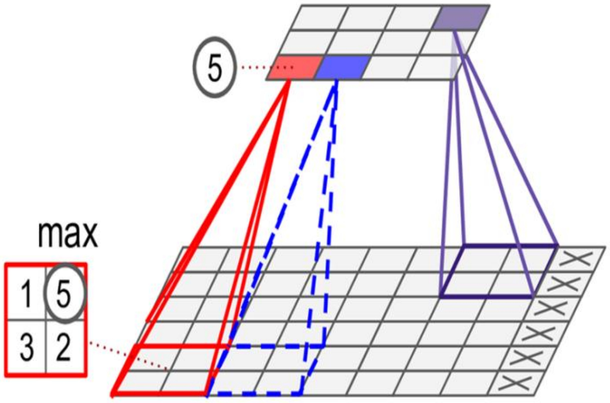
Chapter 08: Using Convolutional Neural Networks for Predictive Analytics

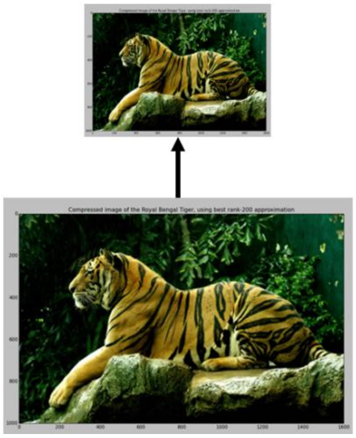


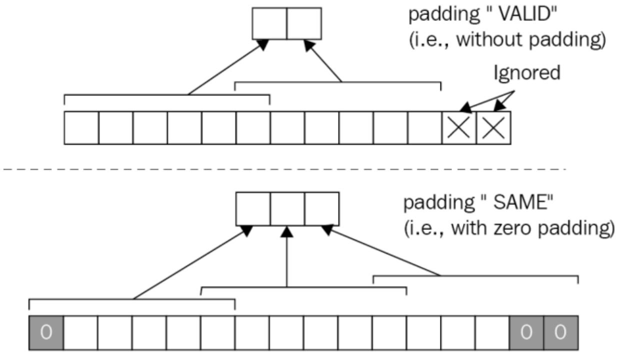


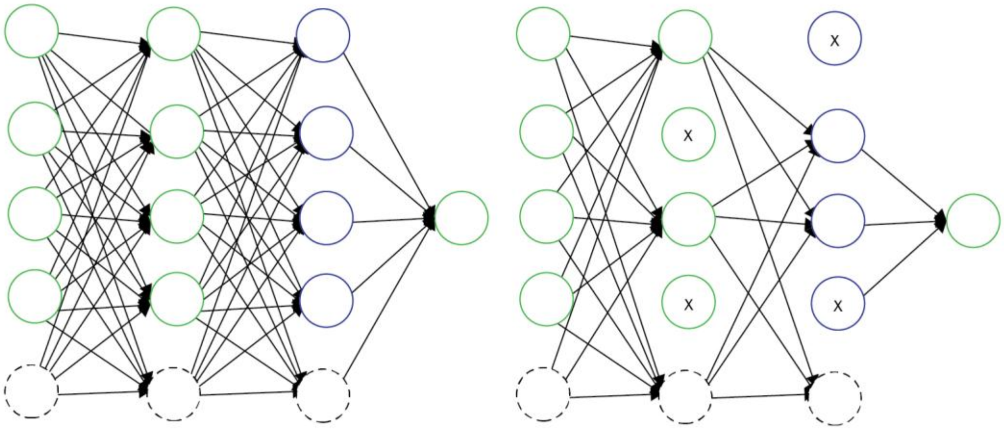






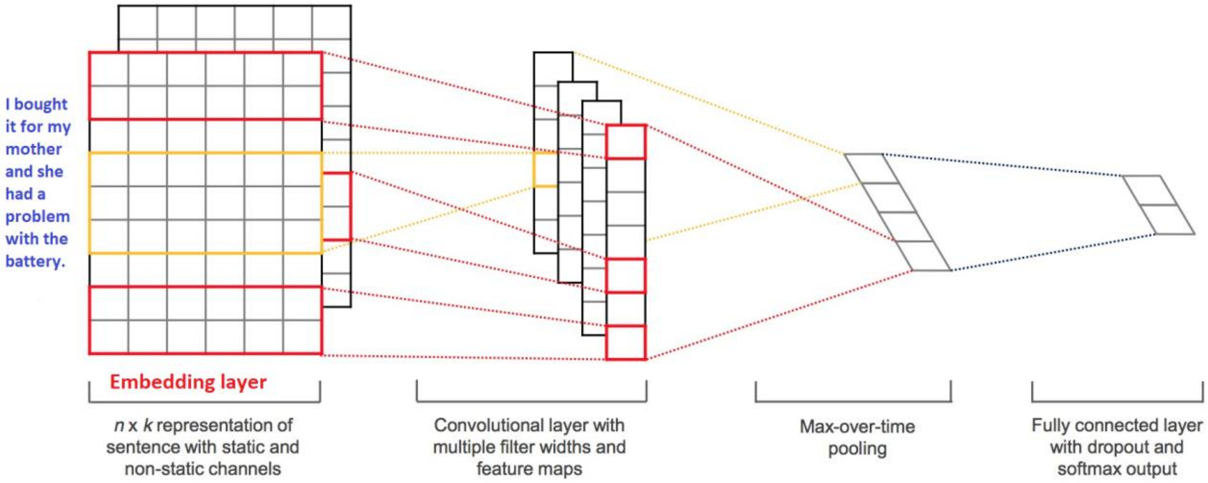


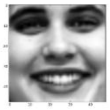


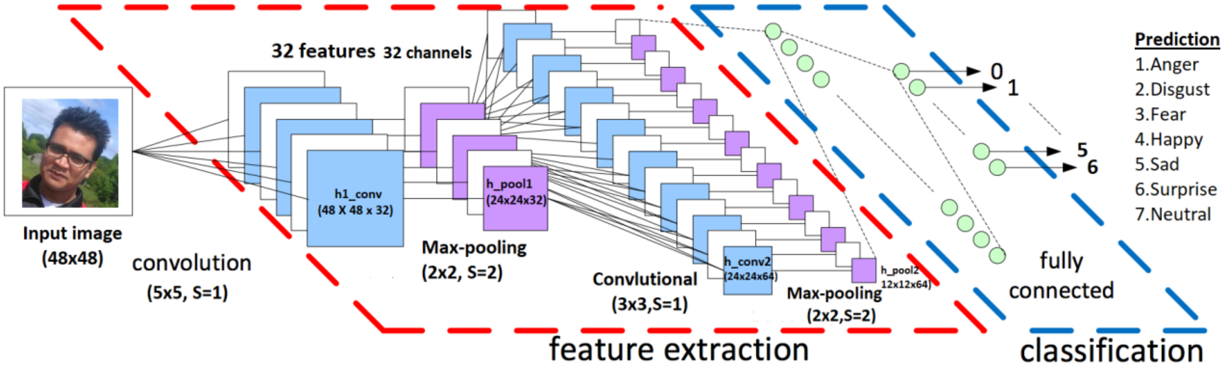


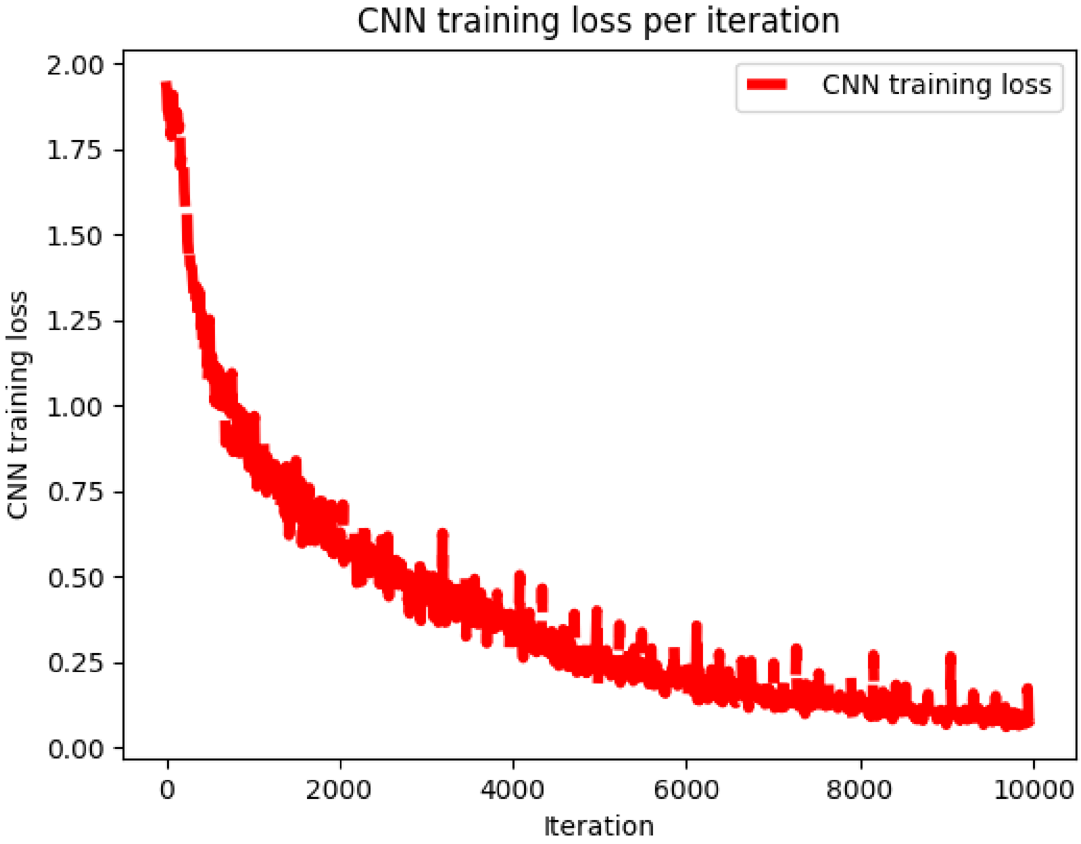
Without dropout

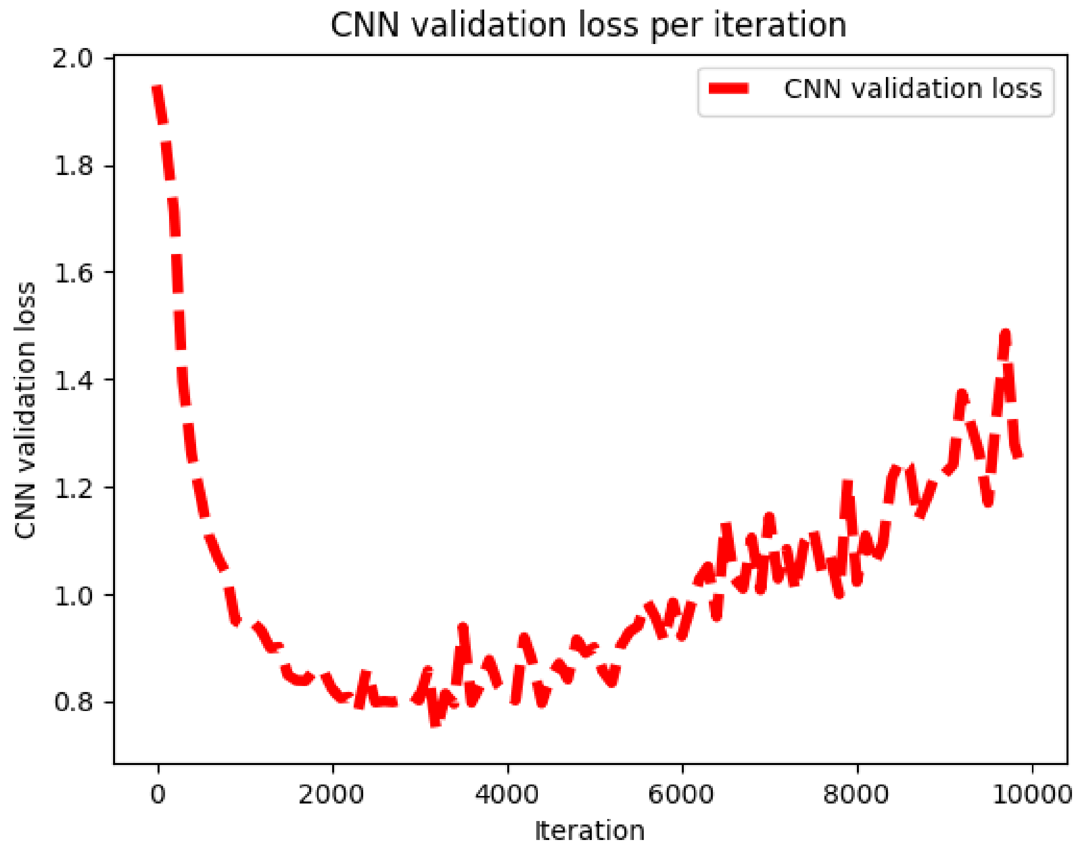
With dropout


I bought it for my mother and she had a problem with the battery.
Embedding layer
n x k representation of sentence with static and non-static channels
Convolutional layer with multiple filter widths and feature maps
Max-over-time pooling
Fully connected layer with dropout and softmax output

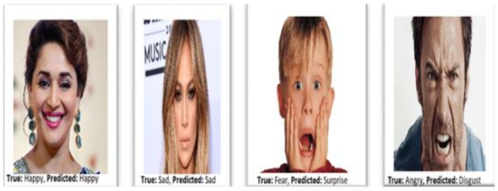


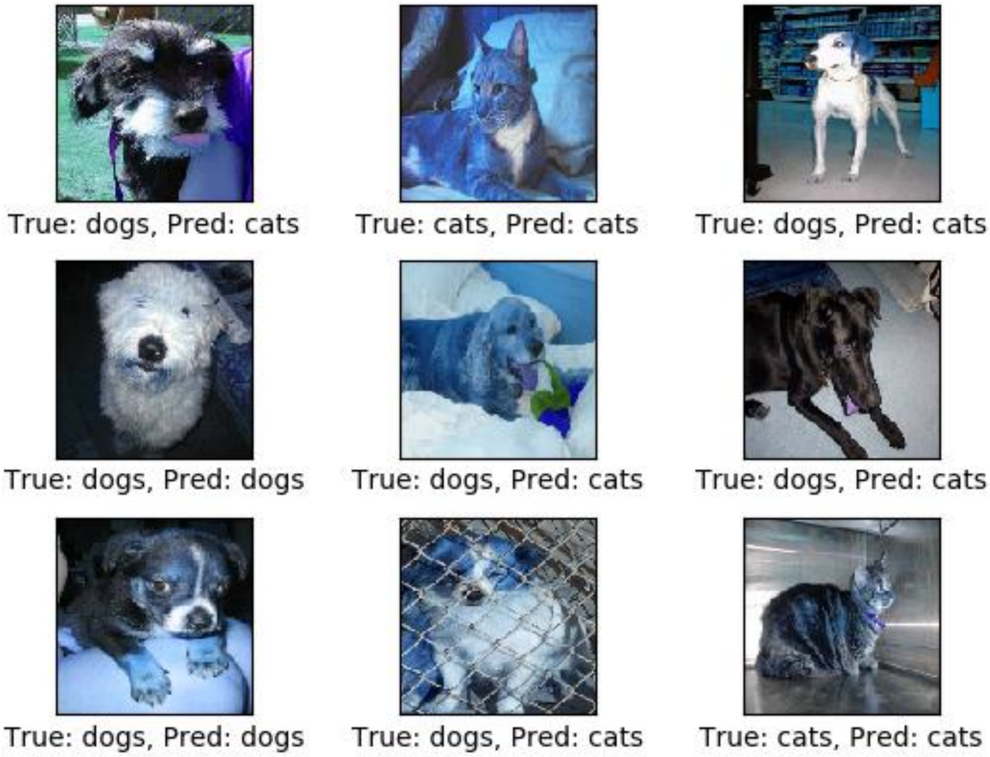

Input image
(48x48)
convolution
(5x5, S=1)
32 features
32 channels
h1_conv
(48 X 48 x 32)
Max-pooling
(2x2, S=2)
h_pool1
(24x24x32)
Convlutional
(3x3,S=1)
h_conv2
(24x24x64)
Max-pooling
(2x2,S=2)
h_pool2
12x12x64)
0
1
5
6
fully
connected
Prediction
1.Anger
2.Disgust
3.Fear
4.Happy
5.Sad
6.Surprise
7.Neutral
feature extraction
classification

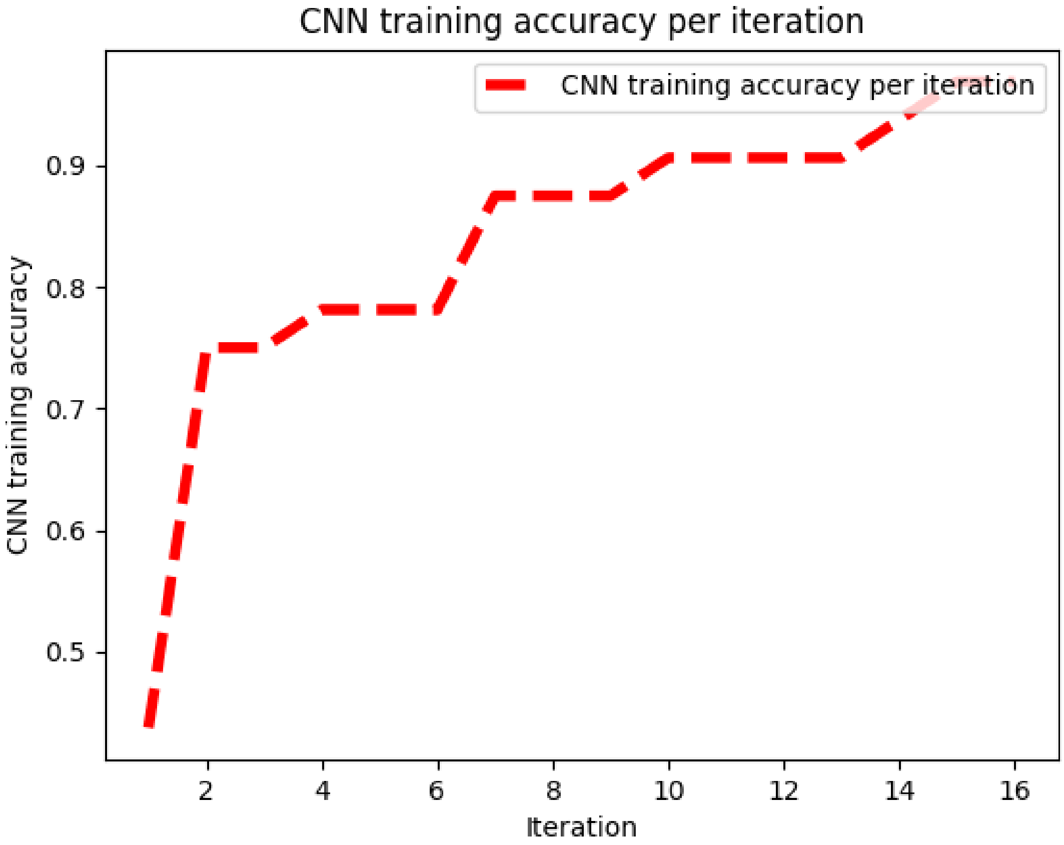

CNN training loss per iteration
CNN training loss
CNN training loss
Iteration
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
0
2000
4000
6000
8000
10000

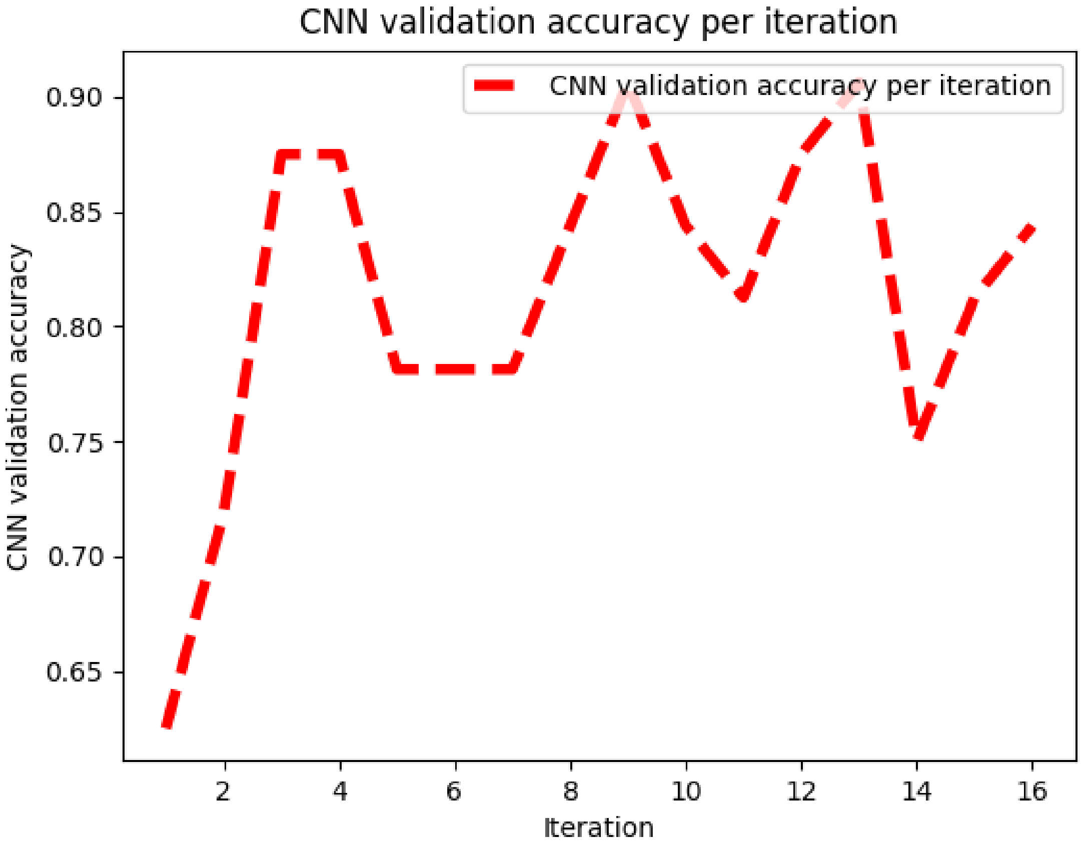

CNN validation loss per iteration
CNN validation loss
2.0
1.8
1.6
1.4
1.2
1.0
0.8
0
2000
4000
6000
8000
10000
Iteration
CNN validation loss

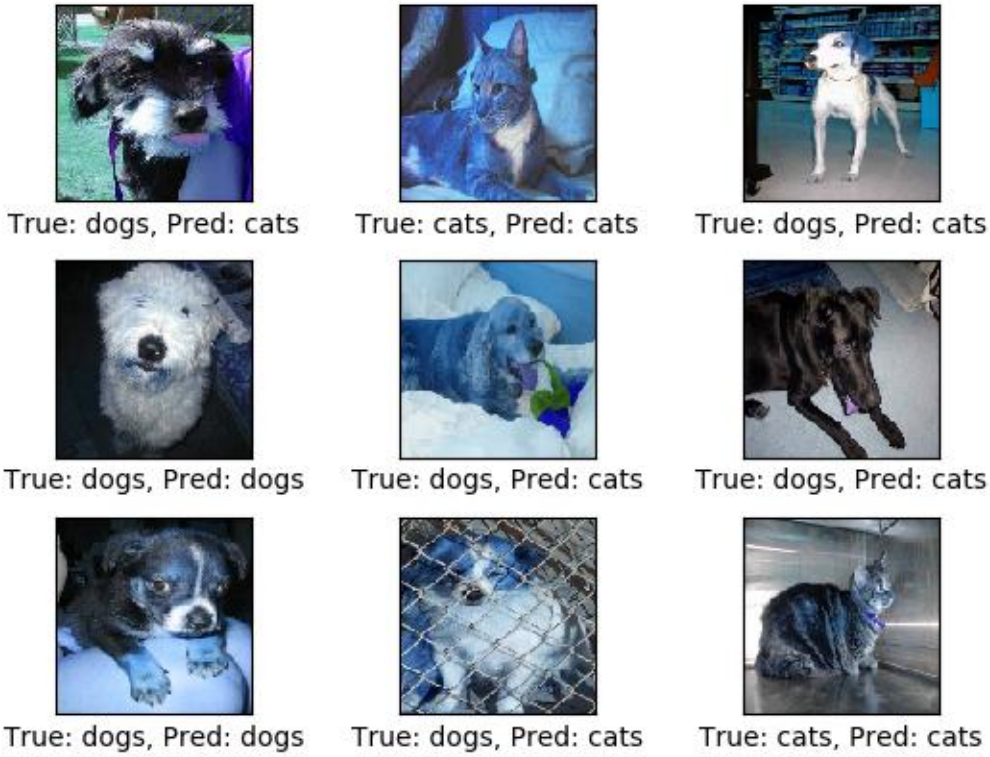
MUSIC


True: Happy, **Predicted:** Happy
True: Sad, **Predicted:** Sad
True: Fear, **Predicted:** Surprise
True: Angry, **Predicted:** Disgust


True: dogs, Pred: cats
True: cats, Pred: cats
True: dogs, Pred: cats
True: dogs, Pred: dogs
True: dogs, Pred: cats
True: dogs, Pred: cats
True: dogs, Pred: dogs
True: dogs, Pred: cats
True: cats, Pred: cats


CNN training accuracy per iteration
CNN training accuracy per iteration
CNN training accuracy
0.5
0.6
0.7
0.8
0.9
Iteration
2
4
6
8
10
12
14
16


CNN validation accuracy per iteration
CNN validation accuracy per iteration
CNN validation accuracy
0.90
0.85
0.80
0.75
0.70
0.65
2
4
6
8
10
12
14
16
Iteration



True: dogs, Pred: cats

True: cats, Pred: cats

True: dogs, Pred: cats

True: dogs, Pred: dogs

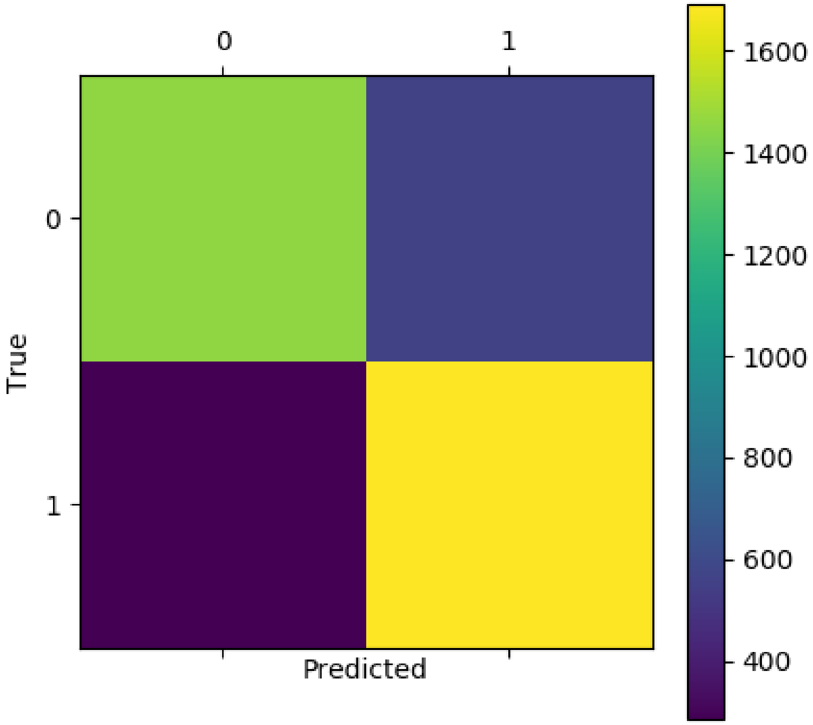
True: dogs, Pred: cats

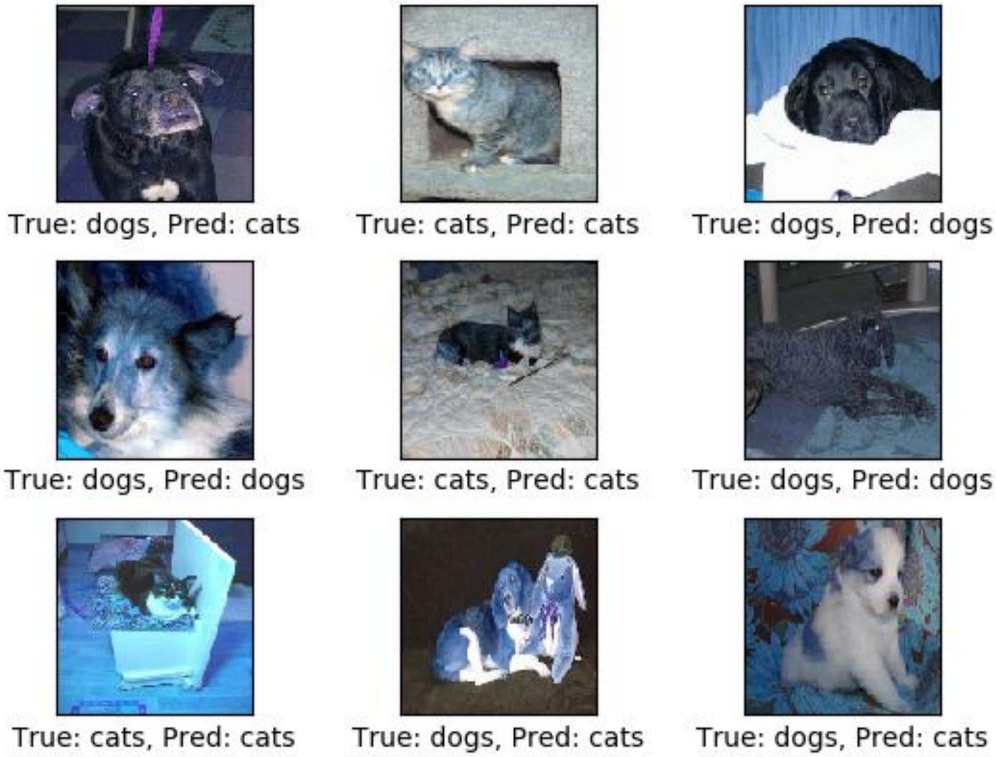
True: dogs, Pred: cats

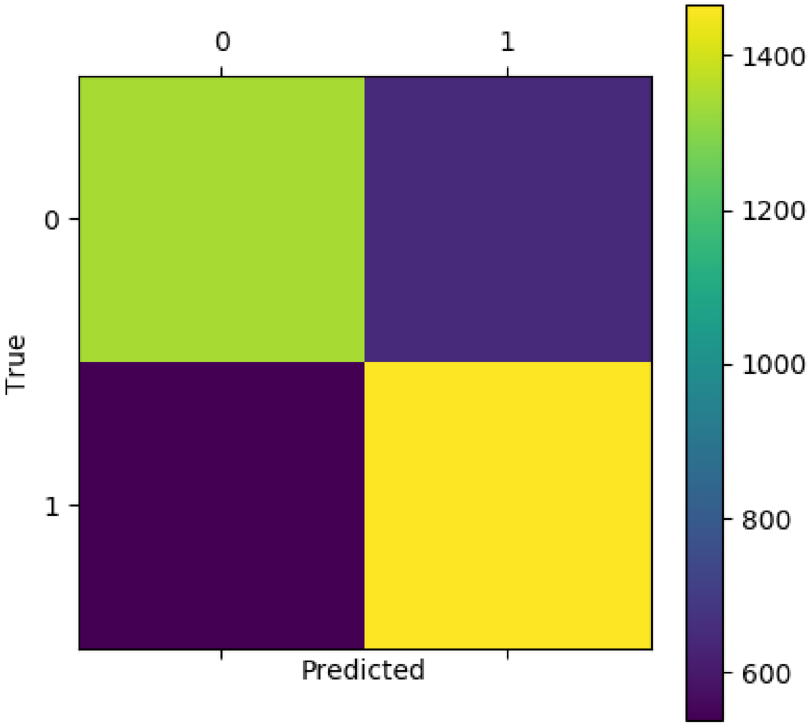
True: dogs, Pred: dogs

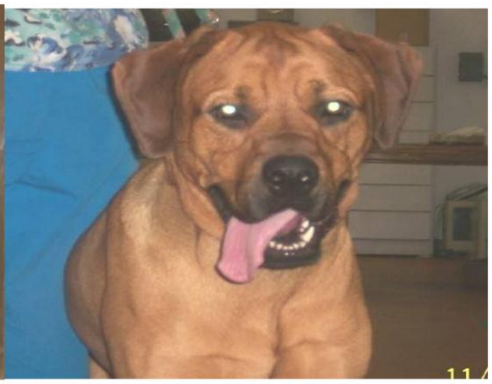
True: dogs, Pred: cats

True: cats, Pred: cats

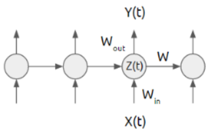

0
1
0
1
True
Predicted
1600
1400
1200
1000
800
600
400

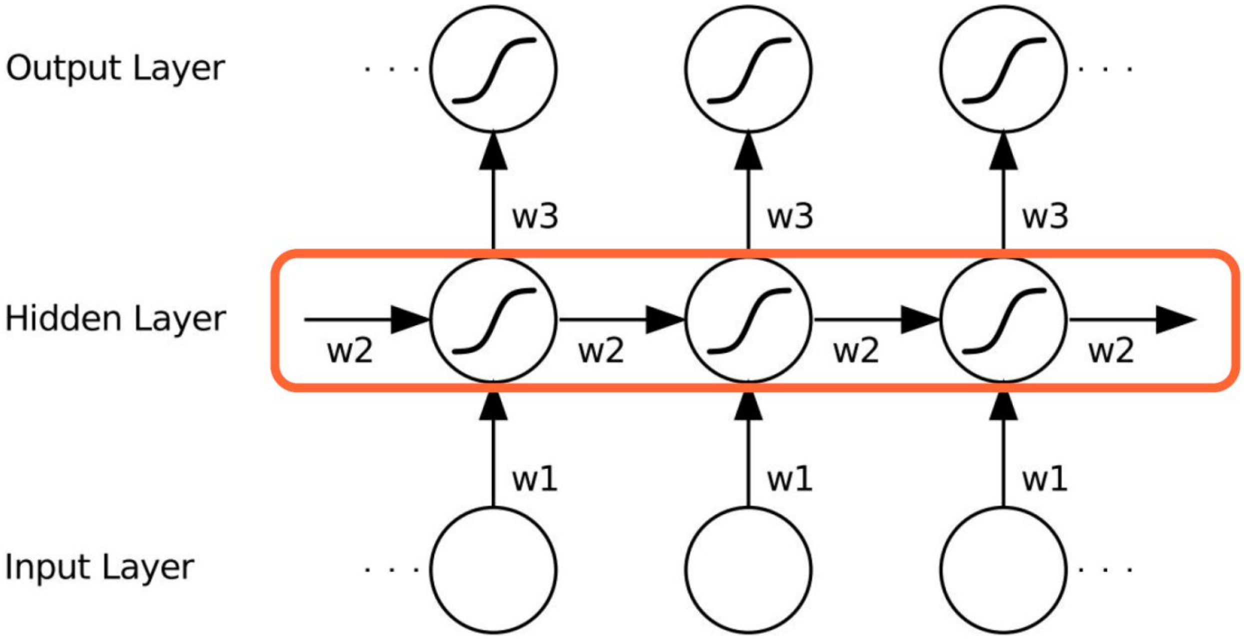

True: dogs, Pred: cats
True: cats, Pred: cats
True: dogs, Pred: dogs
True: dogs, Pred: dogs
True: cats, Pred: cats
True: dogs, Pred: dogs
True: cats, Pred: cats
True: dogs, Pred: cats
True: dogs, Pred: cats

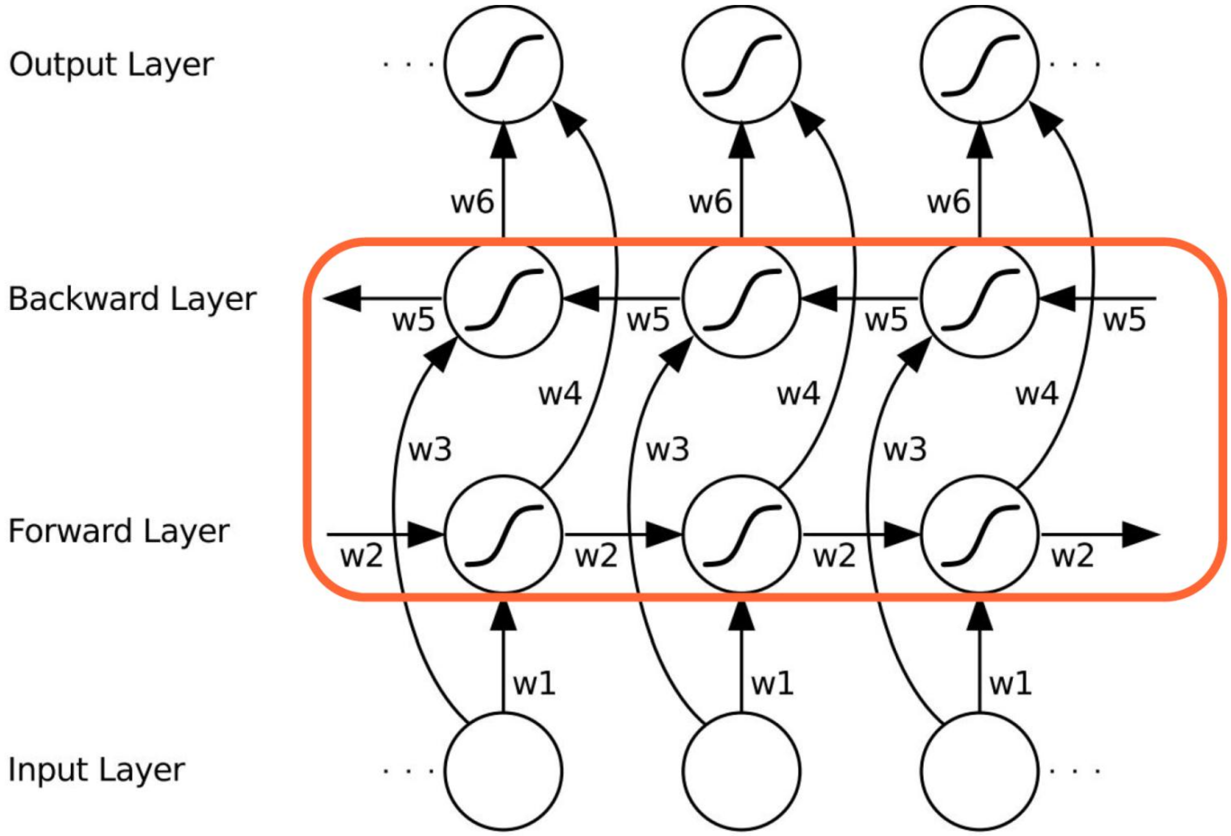

0
1
0
1
True
Predicted
1400
1200
1000
800
600

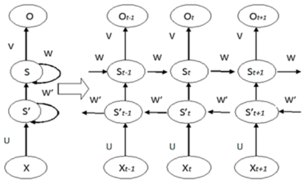


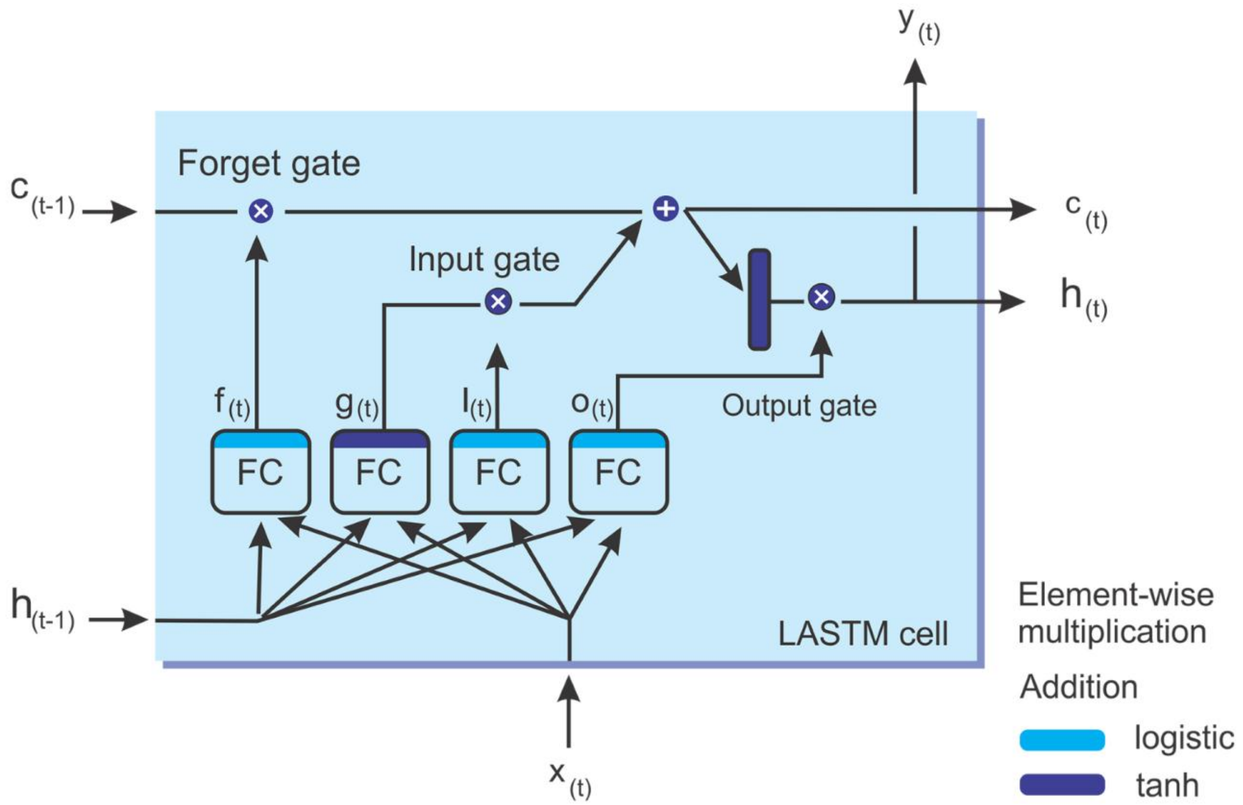
Chapter 09: Using Recurrent Neural Networks for Predictive Analytics

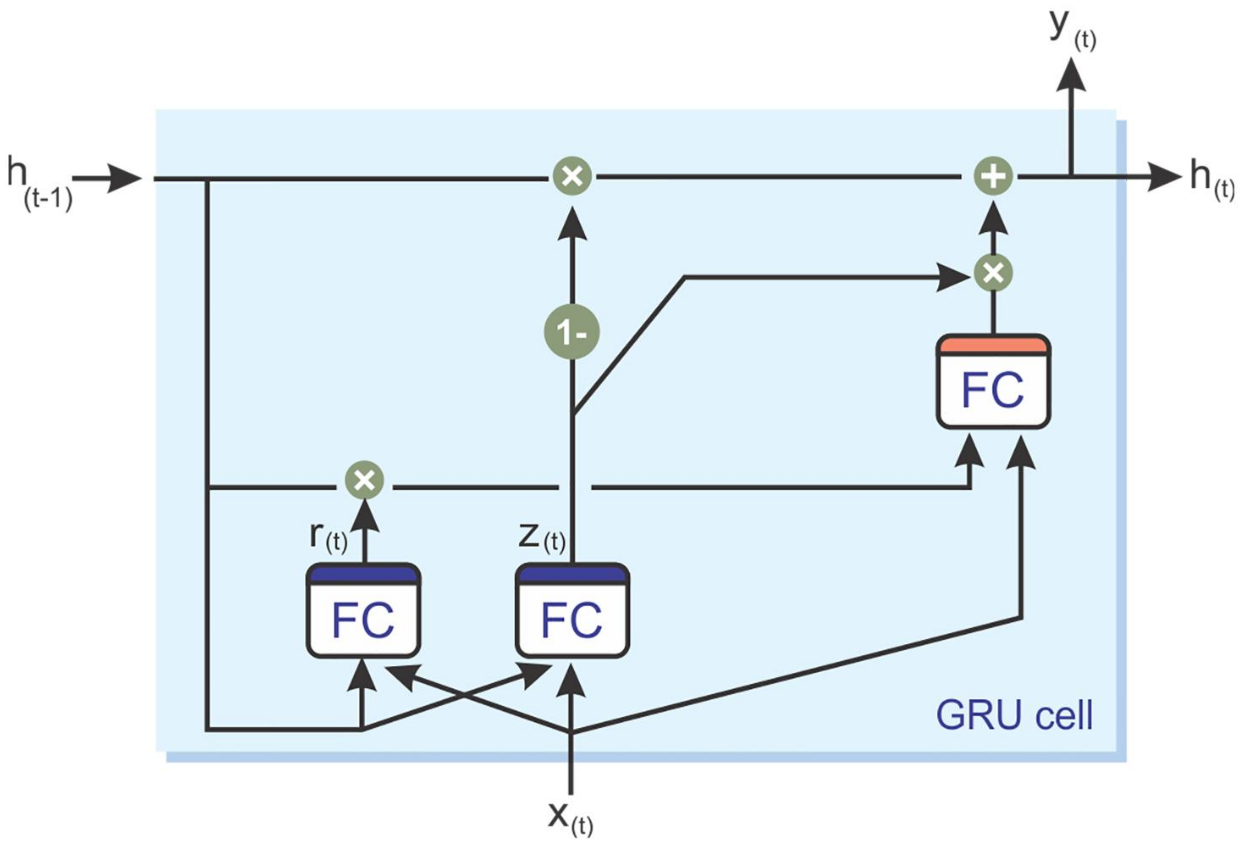


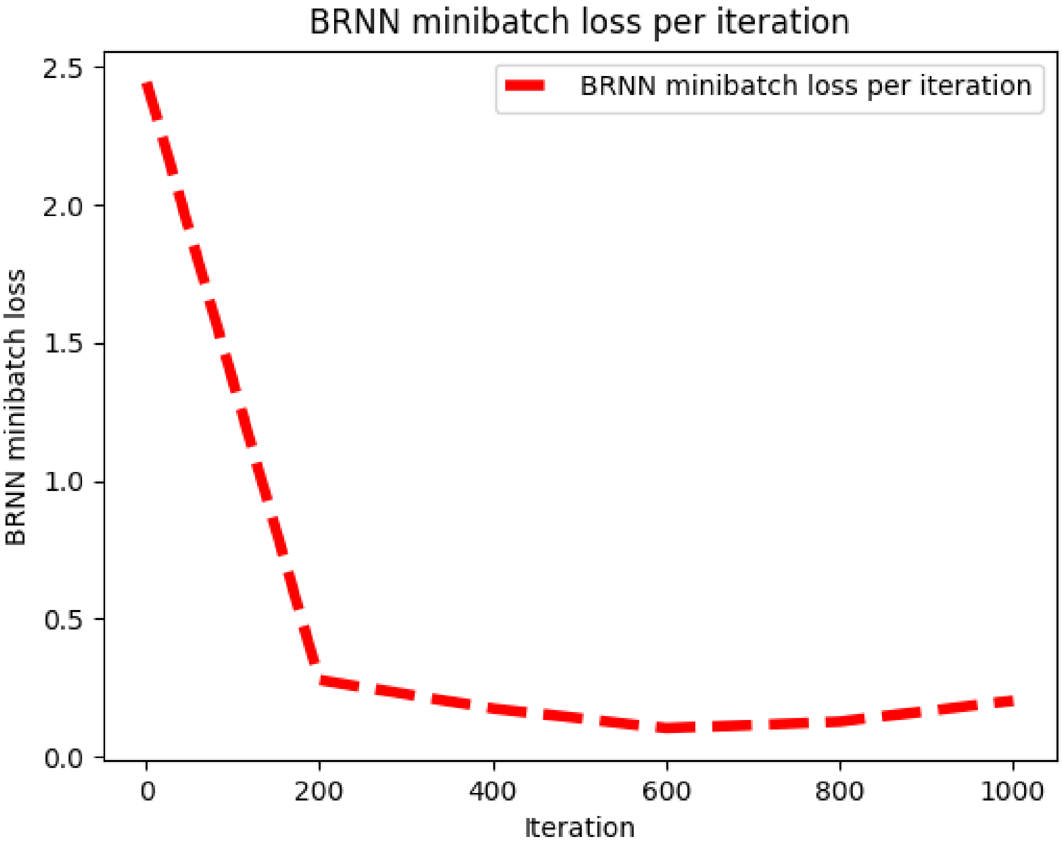


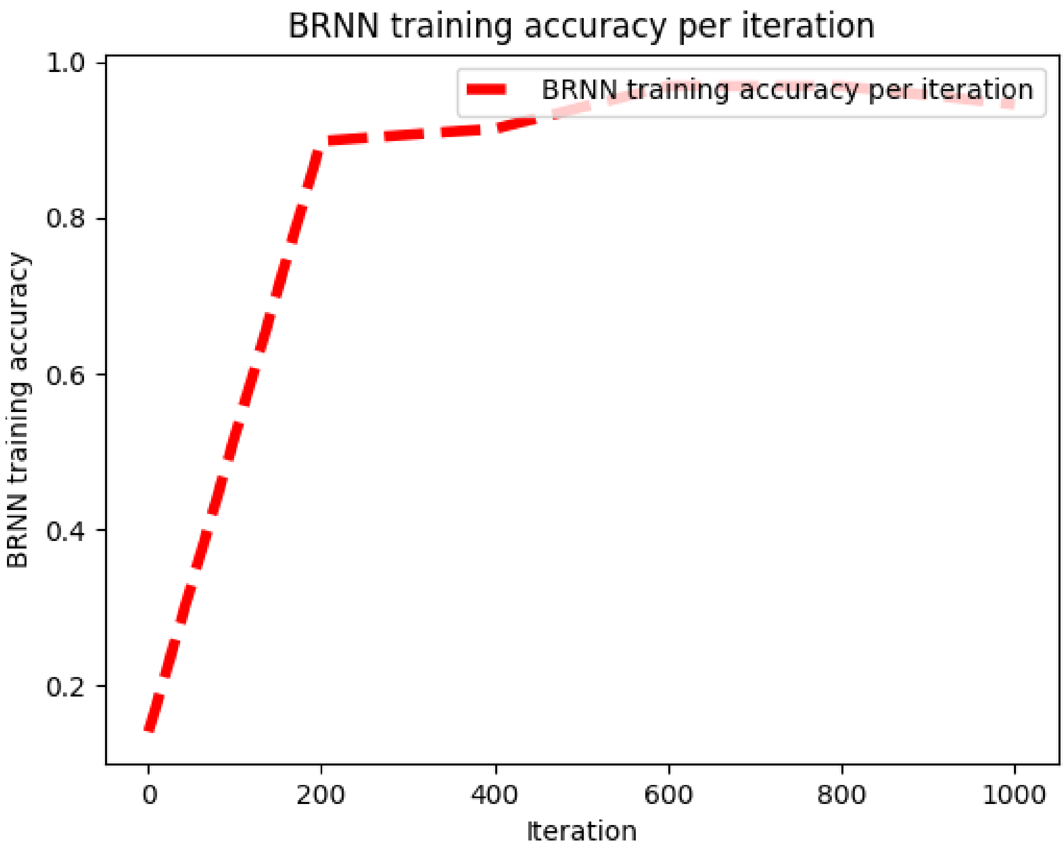

Output Layer
Backward Layer
Forward Layer
Input Layer
w6
w6
w6
w5
w5
w5
w5
w4
w4
w4
w3
w3
w3
w2
w2
w2
w2
w1
w1
w1
· · ·
· · ·
· · ·
· · ·

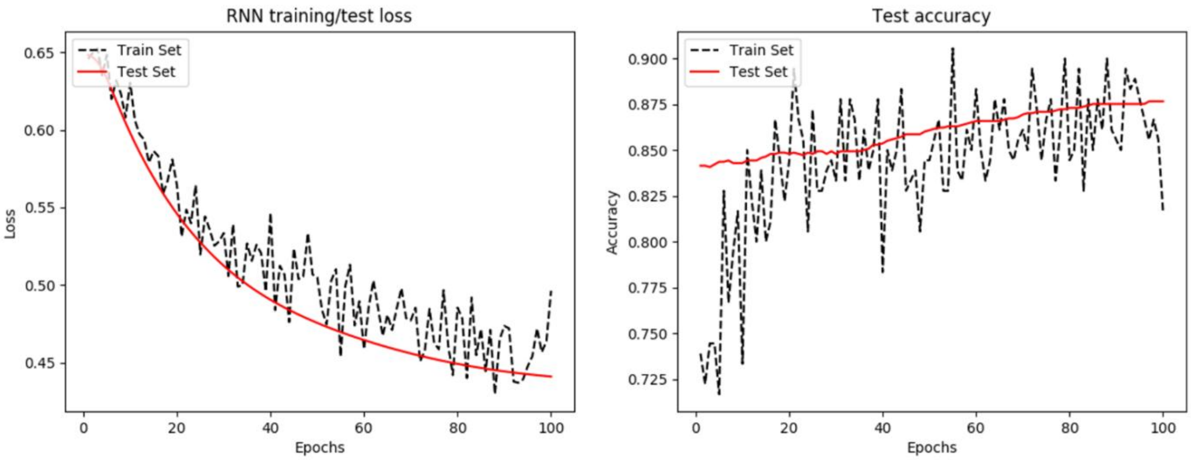

O
V
W
S
W'
S'
U
X
Ot-1
Ot
Ot+1
V
V
V
W
W
W
W
St-1
St
St+1
W'
W'
W'
W'
S't-1
S't
S't+1
U
U
U
Xt-1
Xt
Xt+1


y (t)
Forget gate
c (t-1)
c (t)
Input gate
h (t)
f (t)
g (t)
I (t)
o (t)
Output gate
FC
FC
FC
FC
h (t-1)
LASTM cell
x (t)
Element-wise multiplication
Addition
logistic
tanh

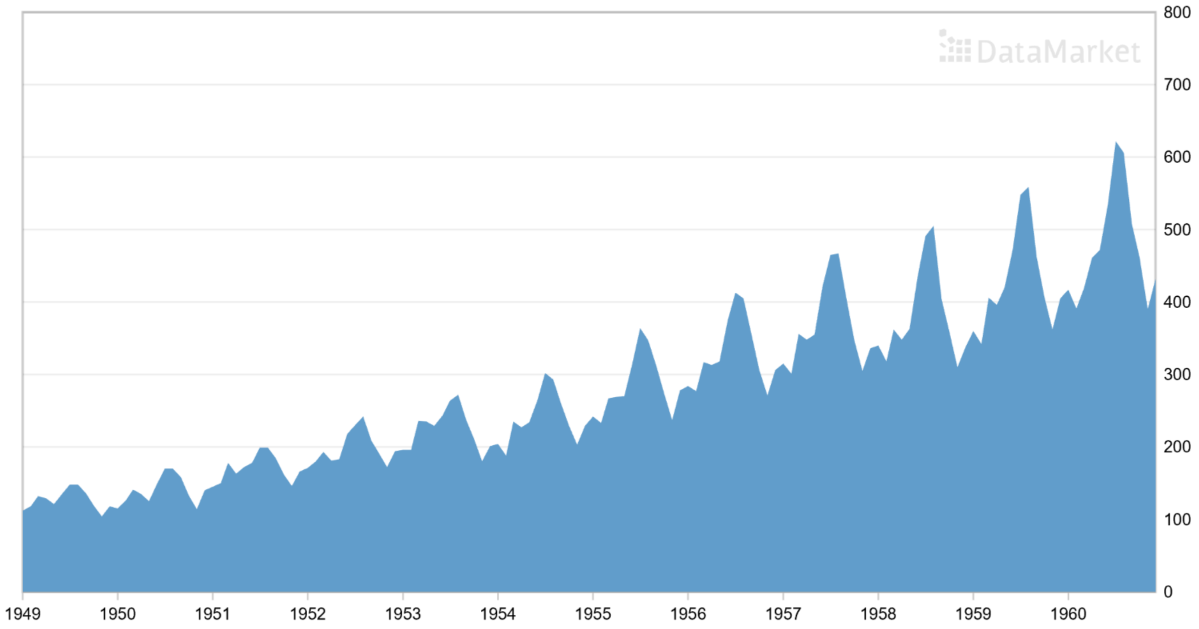

y(t)
h(t-1)
h(t)
1-
FC
r(t)
z(t)
FC
FC
GRU cell
x(t)

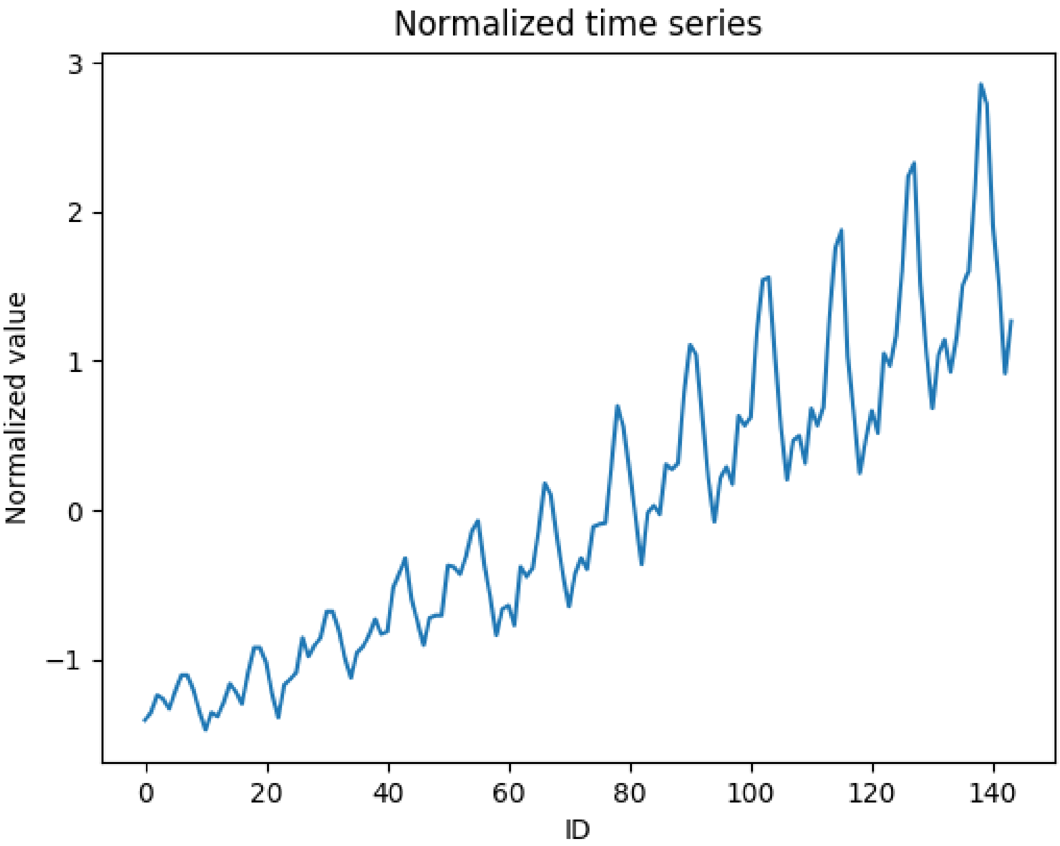

BRNN minibatch loss per iteration
BRNN minibatch loss per iteration
BRNN minibatch loss
2.5
2.0
1.5
1.0
0.5
0.0
0
200
400
600
800
1000
Iteration

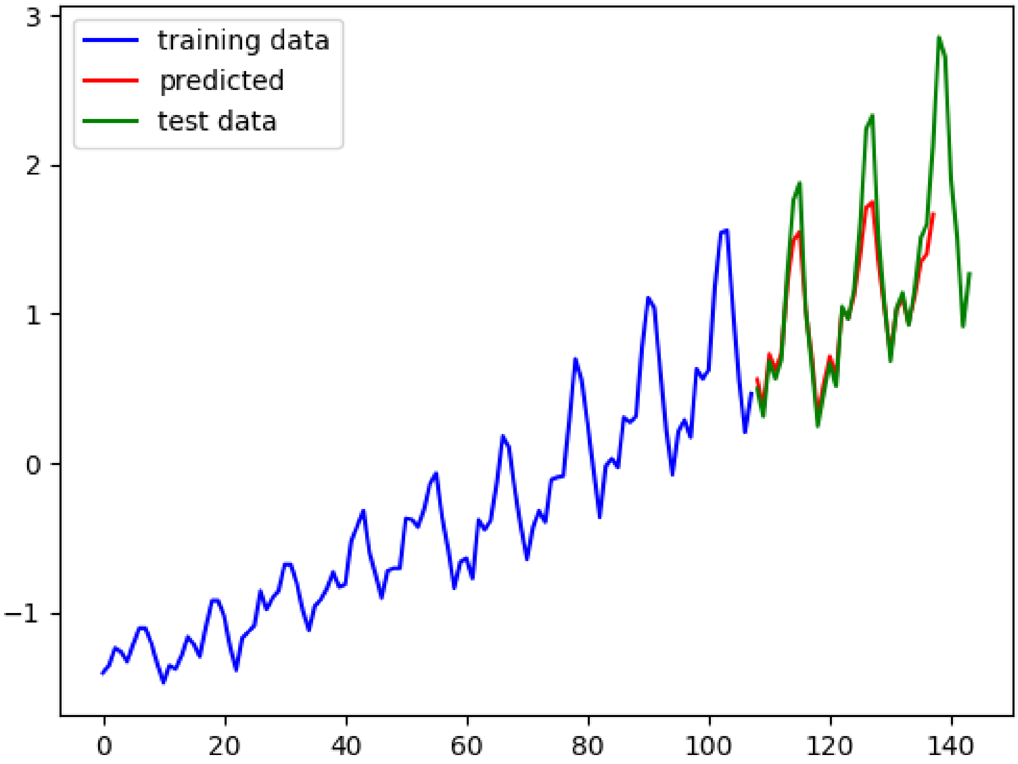

BRNN training accuracy per iteration
BRNN training accuracy per iteration
BRNN training accuracy
1.0
0.8
0.6
0.4
0.2
0
200
400
600
800
1000
Iteration

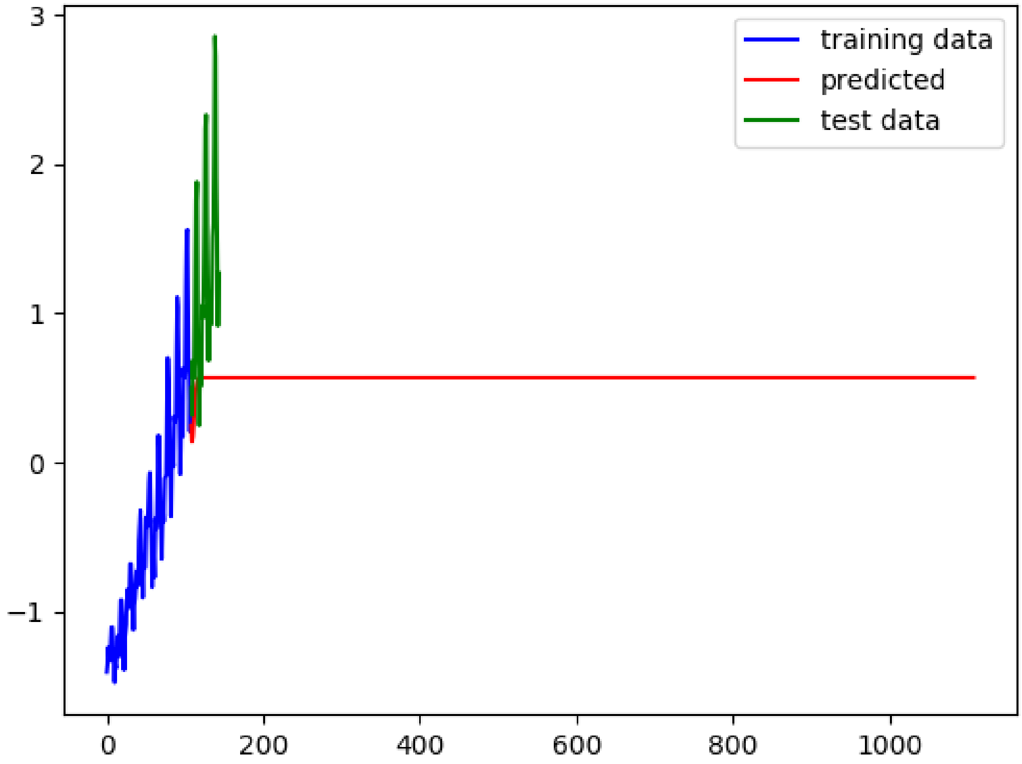

RNN training/test loss
Train Set
Test Set
Loss
0.65
0.60
0.55
0.50
0.45
0
20
40
60
80
100
Epochs
Test accuracy
Train Set
Test Set
Accuracy
0.900
0.875
0.850
0.825
0.800
0.775
0.750
0.725
0
20
40
60
80
100
Epochs

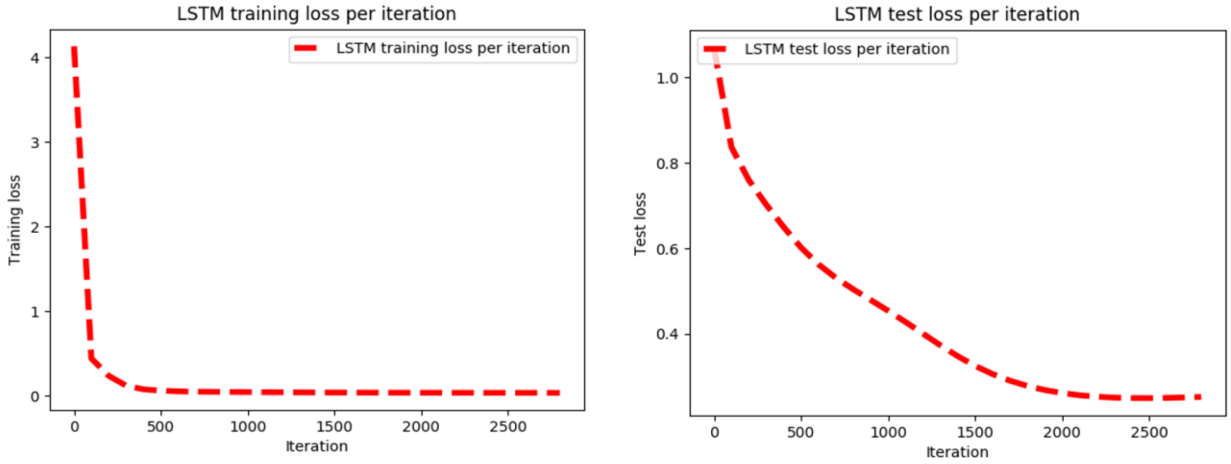
Dataset title	**International airline passengers: monthly totals in thousands. Jan 49 – Dec 60**
Last updated	1 Feb 2014, 19:52
Last updated by source	20 Jun 2012
Provider	Time Series Data Library
Provider source	Box & Jenkins (1976)
Source URL	http://datamarket.com/data/list/?q=provider:tsdl
Units	Thousands of passengers
Dataset metrics	144 fact values in 1 timeseries.
Time granularity	Month
Time range	Jan 1949 – Dec 1960
Language	English
License	Default open license
License summary	This data release is licensed as follows: You may copy and redistribute the data. You may make derivative works from the data. You may use the data for commercial purposes. You may not sublicense the data when redistributing it. You may not redistribute the data under a different license. Source attribution on any use of this data: Must refer source.
Description	Transport and tourism, Source: Box & Jenkins (1976), in file: data/airpass, Description: International airline passengers: monthly totals in thousands. Jan 49 – Dec 60

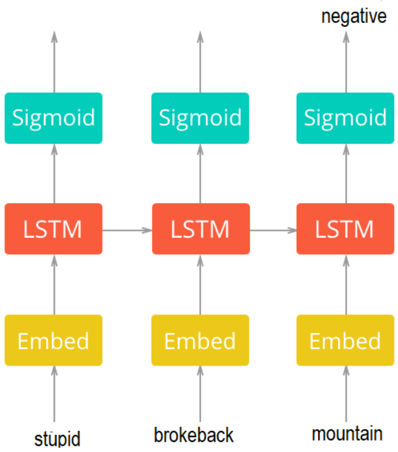


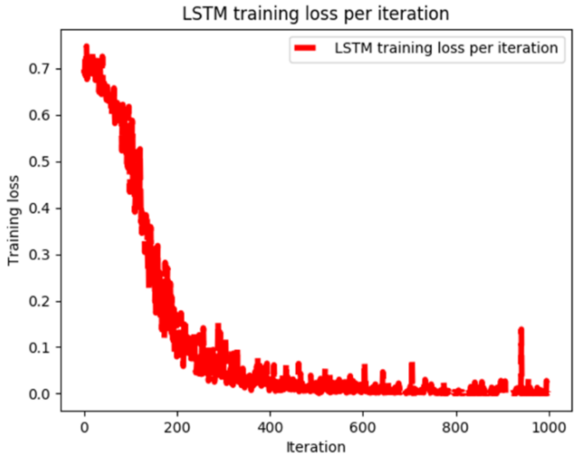

Normalized time series
Normalized value
ID
3
2
1
0
−1
0
20
40
60
80
100
120
140

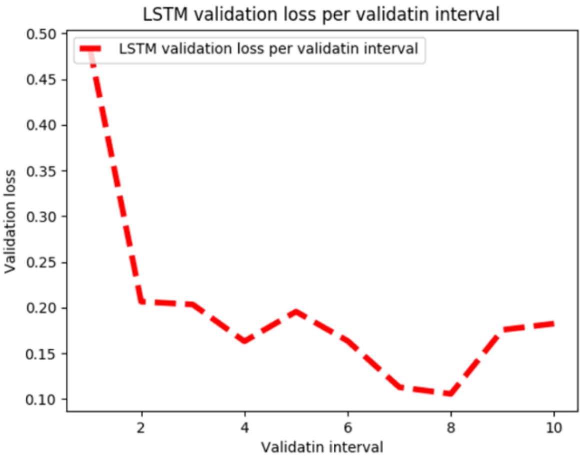

training data
predicted
test data
3
2
1
0
−1
0
20
40
60
80
100
120
140

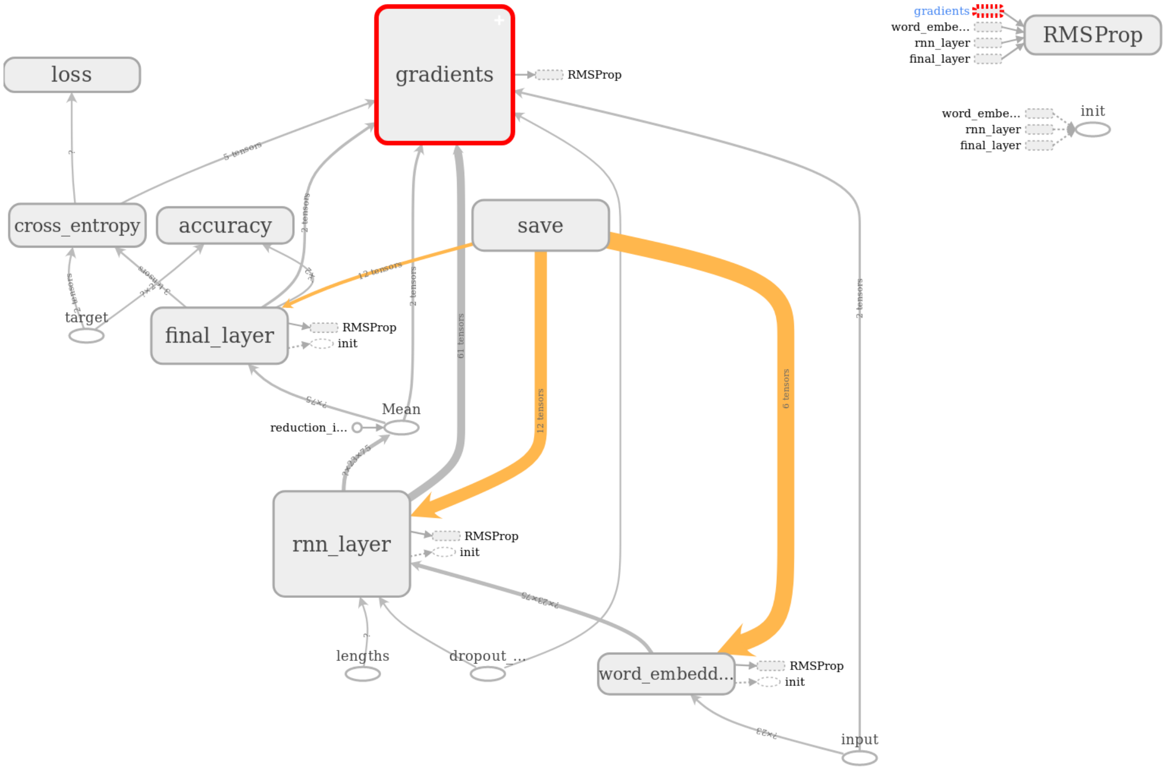

training data
predicted
test data
3
2
1
0
−1
0
200
400
600
800
1000

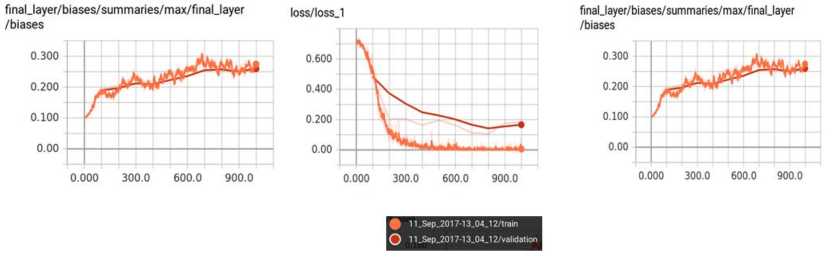

LSTM training loss per iteration
LSTM training loss per iteration
Training loss
Iteration
4
3
2
1
0
0
500
1000
1500
2000
2500
LSTM test loss per iteration
LSTM test loss per iteration
Test loss
Iteration
1.0
0.8
0.6
0.4
0
500
1000
1500
2000
2500


negative
Sigmoid
Sigmoid
Sigmoid
LSTM
LSTM
LSTM
Embed
Embed
Embed
stupid
brokeback
mountain

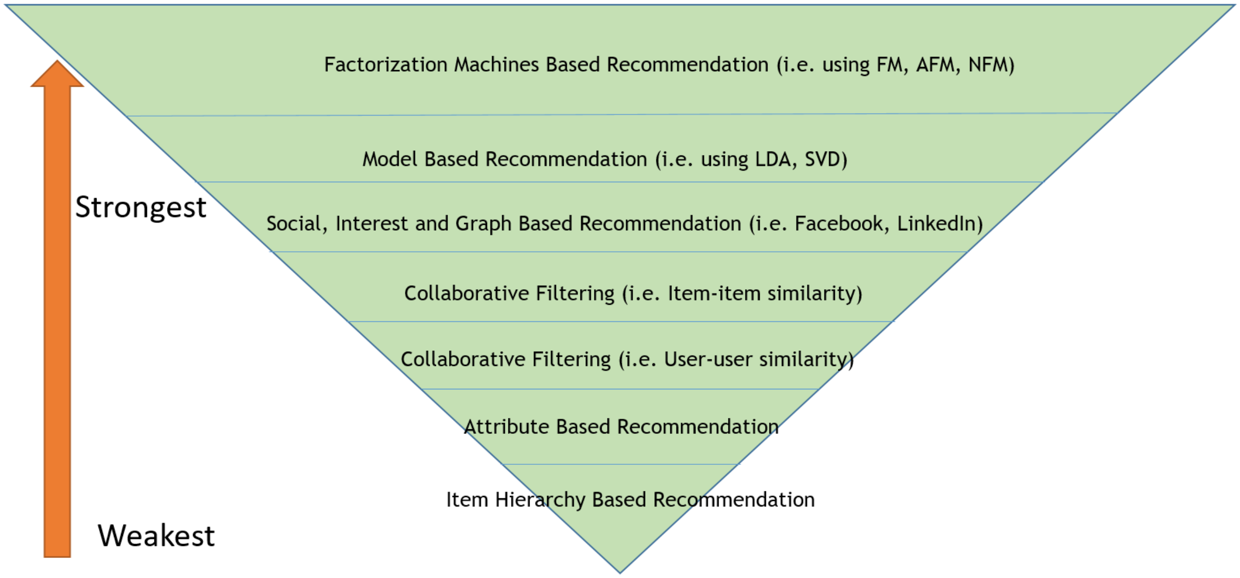

LSTM training loss per iteration
LSTM training loss per iteration
Training loss
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0
200
400
600
800
1000
Iteration

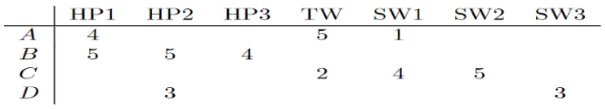

LSTM validation loss per validatin interval
LSTM validation loss per validatin interval
Validation loss
0.10
0.15
0.20
0.25
0.30
0.35
0.40
0.45
0.50
2
4
6
8
10
Validatin interval


gradients
RMSProp
loss
cross_entropy
accuracy
save
5 tensors
2 tensors
12 tensors
61 tensors
6 tensors
target
final_layer
RMSProp
init
Mean
reduction_i...
rnn_layer
RMSProp
init
lengths
dropout_...
word_embedd...
RMSProp
init
input
gradients
word_embe...
rnn_layer
final_layer
RMSProp
word_embe...
rnn_layer
final_layer
init

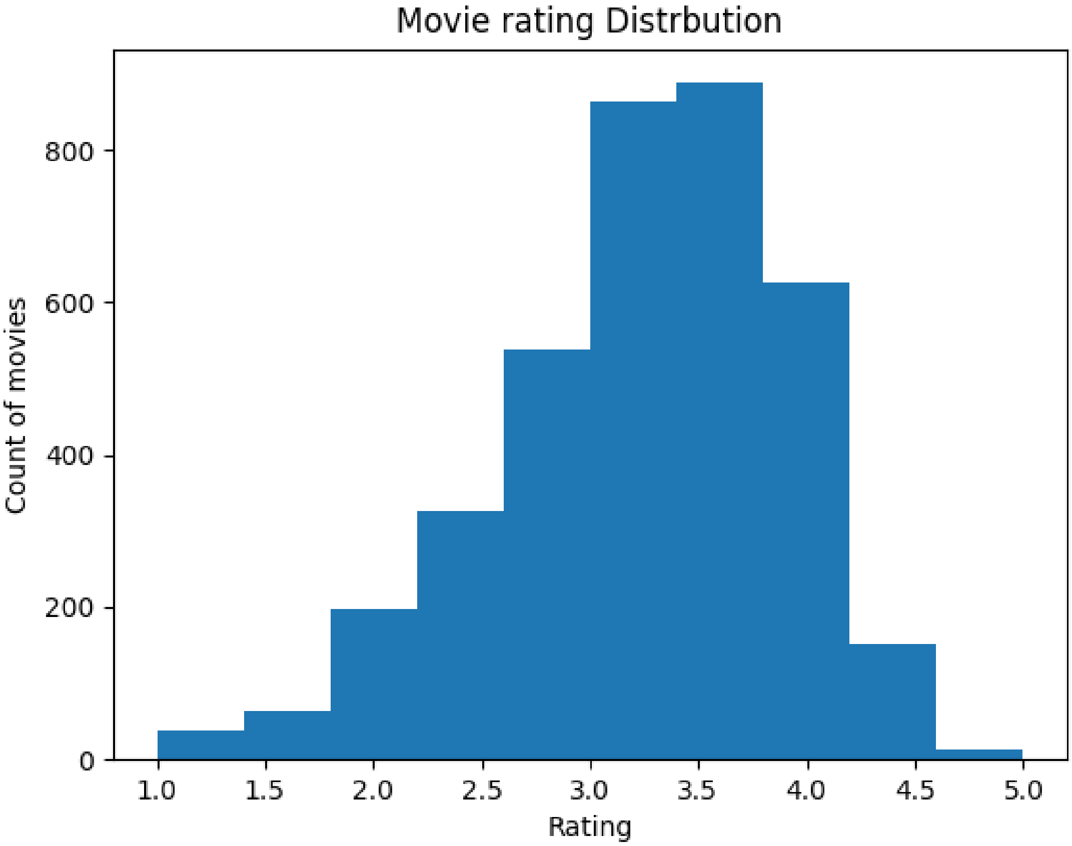

final_layer/biases/summaries/max/final_layer
/biases
0.300
0.200
0.100
0.00
0.000
300.0
600.0
900.0
loss/loss_1
0.600
0.400
0.200
0.00
0.000
300.0
600.0
900.0
final_layer/biases/summaries/max/final_layer
/biases
0.300
0.200
0.100
0.00
0.000
300.0
600.0
900.0
11_Sep_2017-13_04_12/train
11_Sep_2017-13_04_12/validation

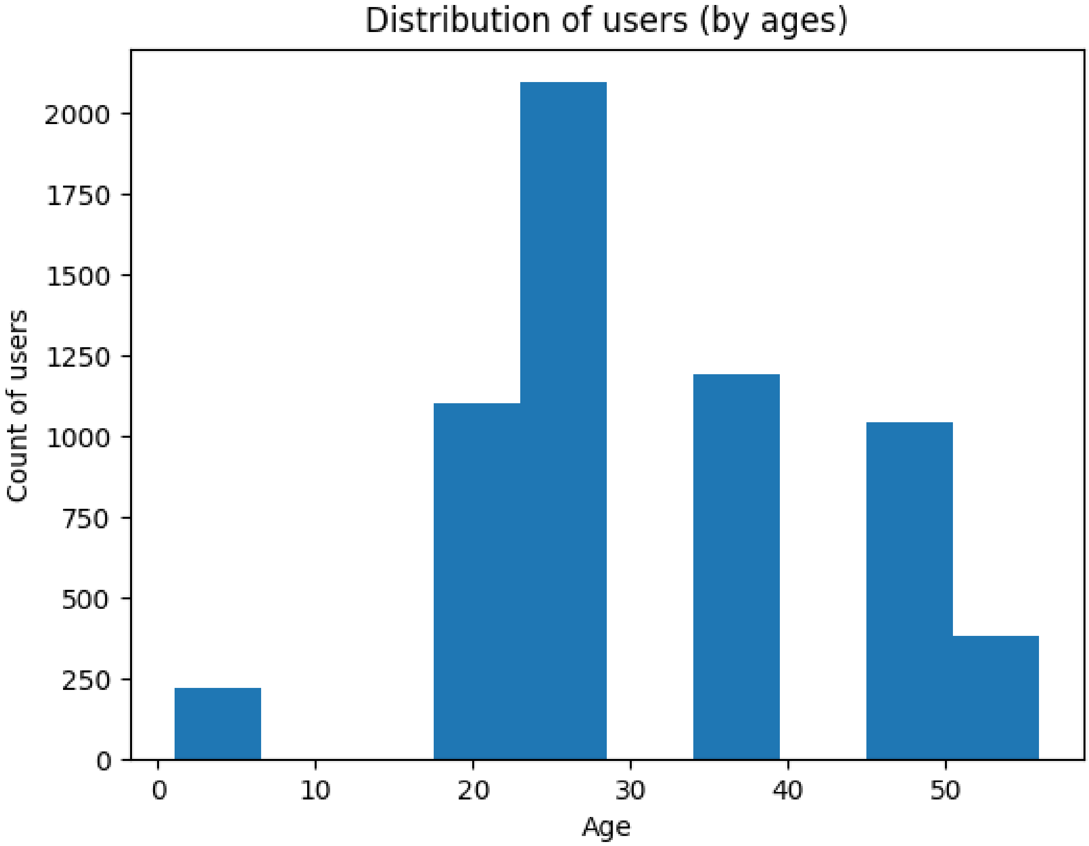
Chapter 10: Recommendation Systems for Predictive Analytics

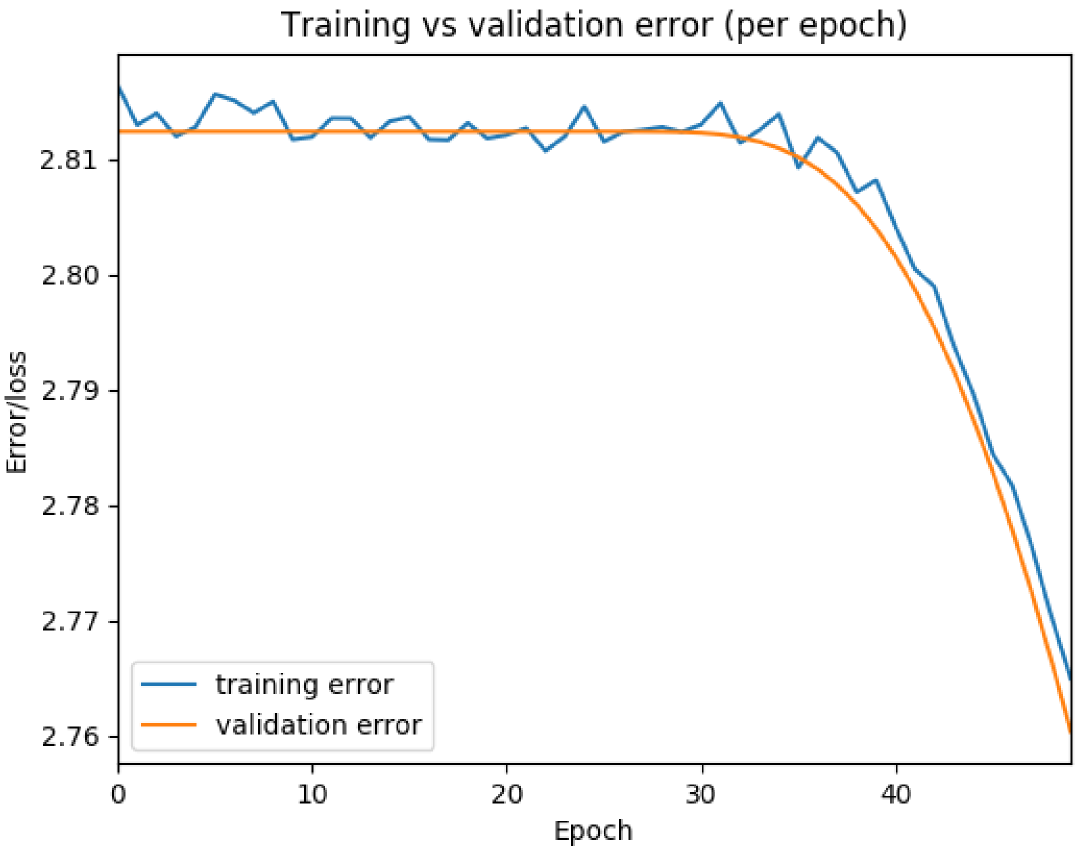

Factorization Machines Based Recommendation (i.e. using FM, AFM, NFM)
Model Based Recommendation (i.e. using LDA, SVD)
Strongest
Social, Interest and Graph Based Recommendation (i.e. Facebook, LinkedIn)
Collaborative Filtering (i.e. Item-item similarity)
Collaborative Filtering (i.e. User-user similarity)
Attribute Based Recommendation
Item Hierarchy Based Recommendation
Weakest

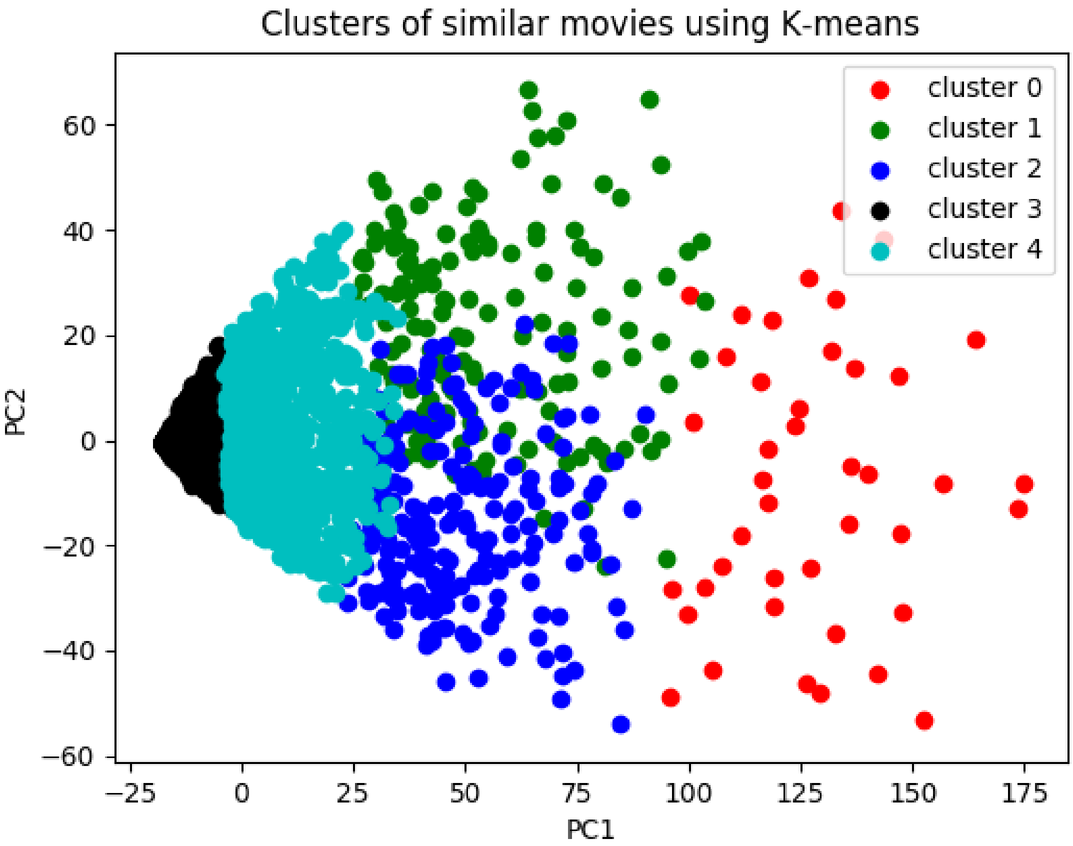


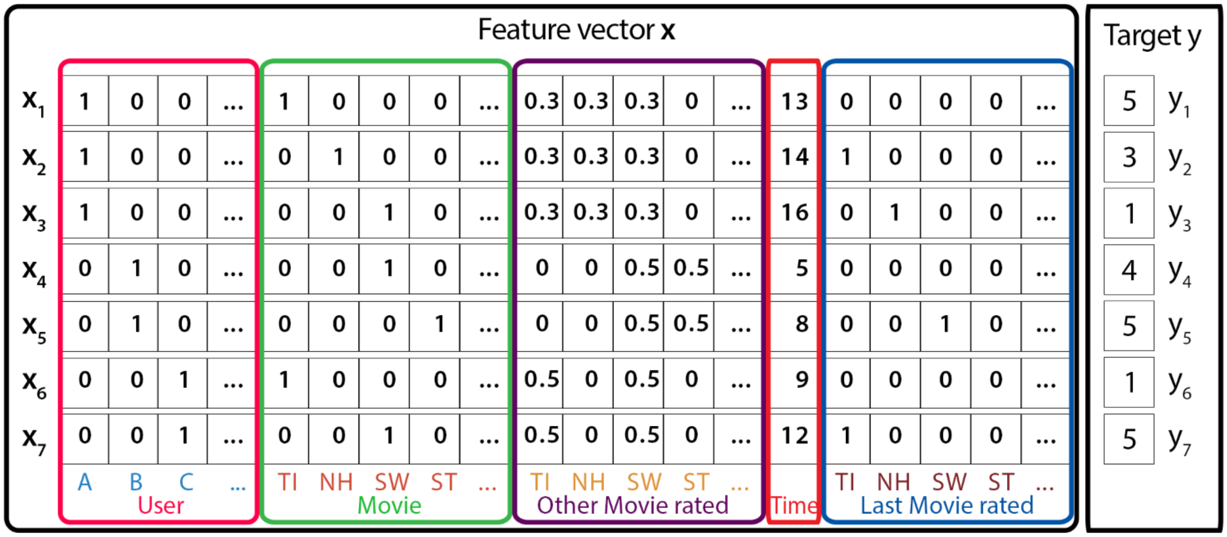
	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	4			5	1		
B	5	5	4				
C				2	4	5	
D		3					3


Movie rating Distrbution
Count of movies
0
200
400
600
800
Rating
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0


Distribution of users (by ages)
Count of users
2000
1750
1500
1250
1000
750
500
250
0
0
10
20
30
40
50
Age

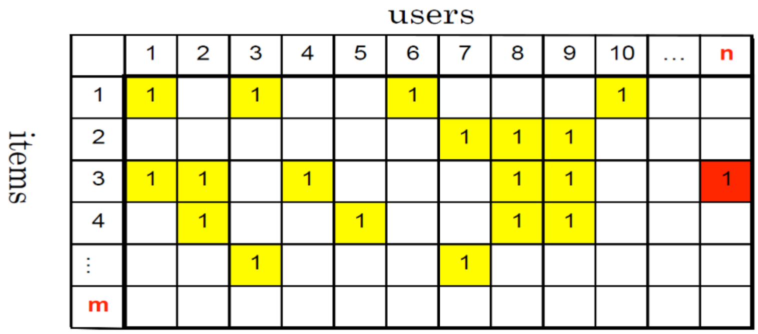

Training vs validation error (per epoch)
Error/loss
2.81
2.80
2.79
2.78
2.77
2.76
0
10
20
30
40
Epoch
training error
validation error


Clusters of similar movies using K-means
cluster 0
cluster 1
cluster 2
cluster 3
cluster 4
PC2
PC1
60
40
20
0
−20
−40
−60
−25
0
25
50
75
100
125
150
175



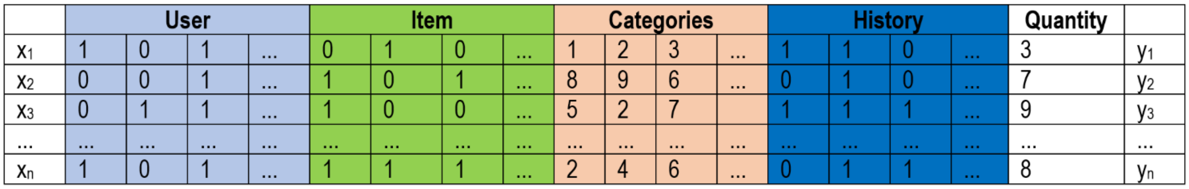
Feature vector **x**

	User				Movie					Other Movie rated					Time	Last Movie rated					Target y	
	A	B	C	...	TI	NH	SW	ST	...	TI	NH	SW	ST	...		TI	NH	SW	ST	...		
x_1	1	0	0	...	1	0	0	0	...	0.3	0.3	0.3	0	...	13	0	0	0	0	...	5	y_1
x_2	1	0	0	...	0	1	0	0	...	0.3	0.3	0.3	0	...	14	1	0	0	0	...	3	y_2
x_3	1	0	0	...	0	0	1	0	...	0.3	0.3	0.3	0	...	16	0	1	0	0	...	1	y_3
x_4	0	1	0	...	0	0	1	0	...	0	0	0.5	0.5	...	5	0	0	0	0	...	4	y_4
x_5	0	1	0	...	0	0	0	1	...	0	0	0.5	0.5	...	8	0	0	1	0	...	5	y_5
x_6	0	0	1	...	1	0	0	0	...	0.5	0	0.5	0	...	9	0	0	0	0	...	1	y_6
x_7	0	0	1	...	0	0	1	0	...	0.5	0	0.5	0	...	12	1	0	0	0	...	5	y_7

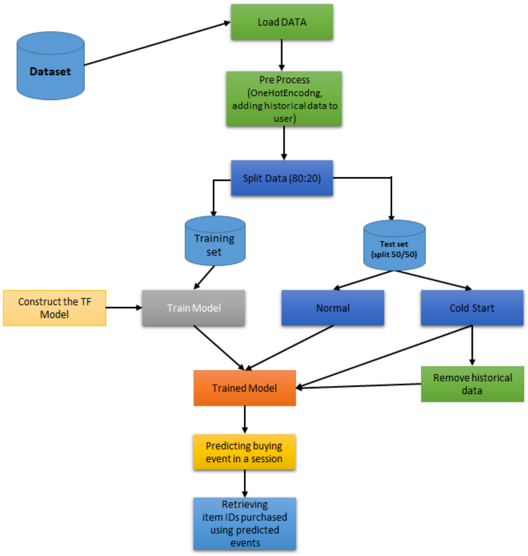


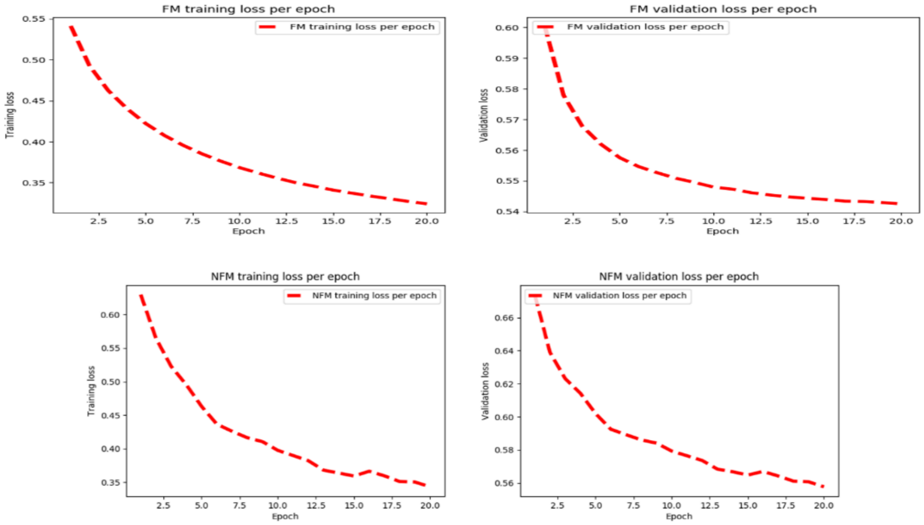
users

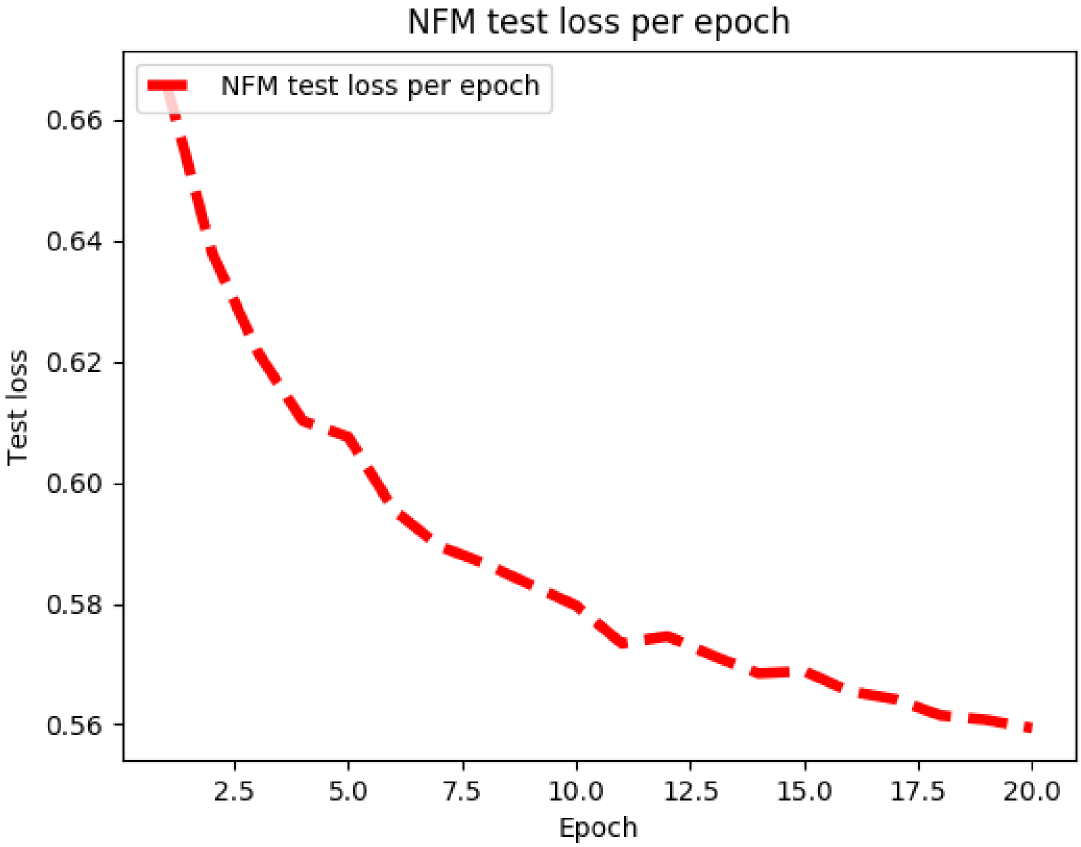
items	1	2	3	4	5	6	7	8	9	10	...	n
1	1		1			1				1		
2							1	1	1			
3	1	1		1				1	1			1
4		1			1			1	1			
⋮			1				1					
m												



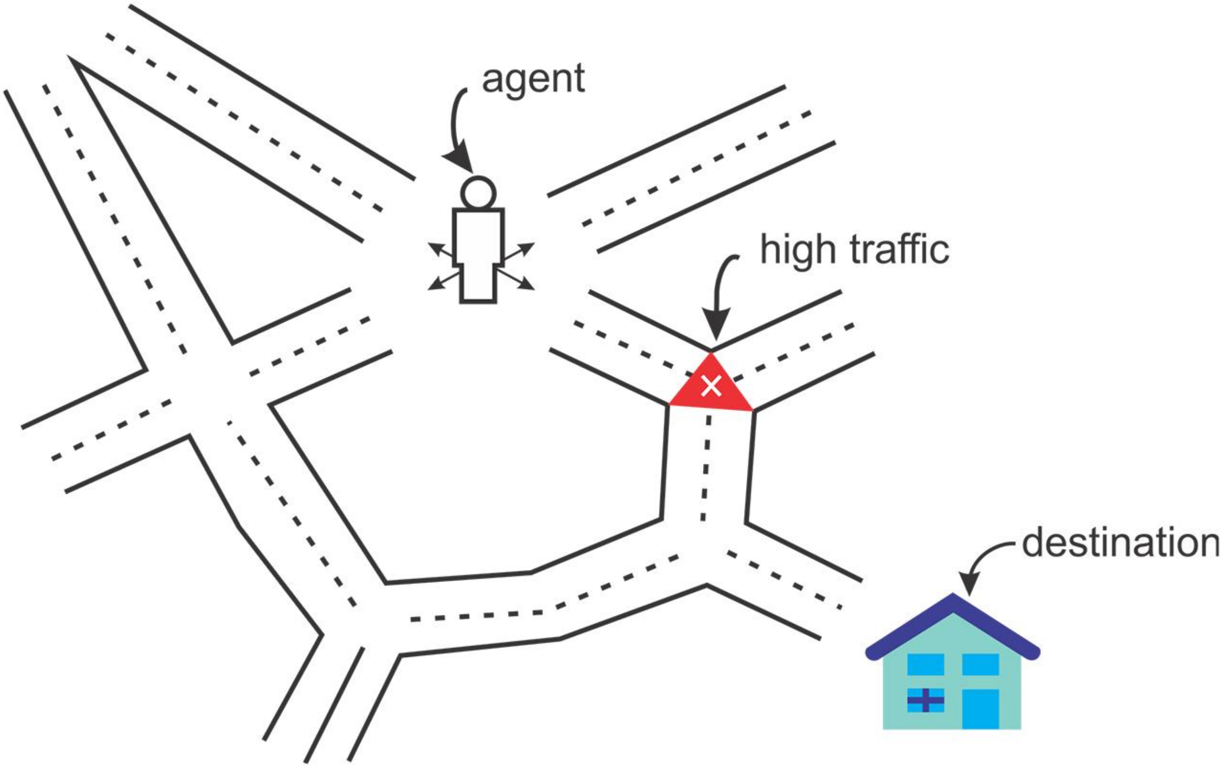
	User				Item				Categories				History				Quantity	
x_1	1	0	1	...	0	1	0	...	1	2	3	...	1	1	0	...	3	y_1
x_2	0	0	1	...	1	0	1	...	8	9	6	...	0	1	0	...	7	y_2
x_3	0	1	1	...	1	0	0	...	5	2	7		1	1	1	...	9	y_3
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
x_n	1	0	1	...	1	1	1	...	2	4	6	...	0	1	1	...	8	y_n

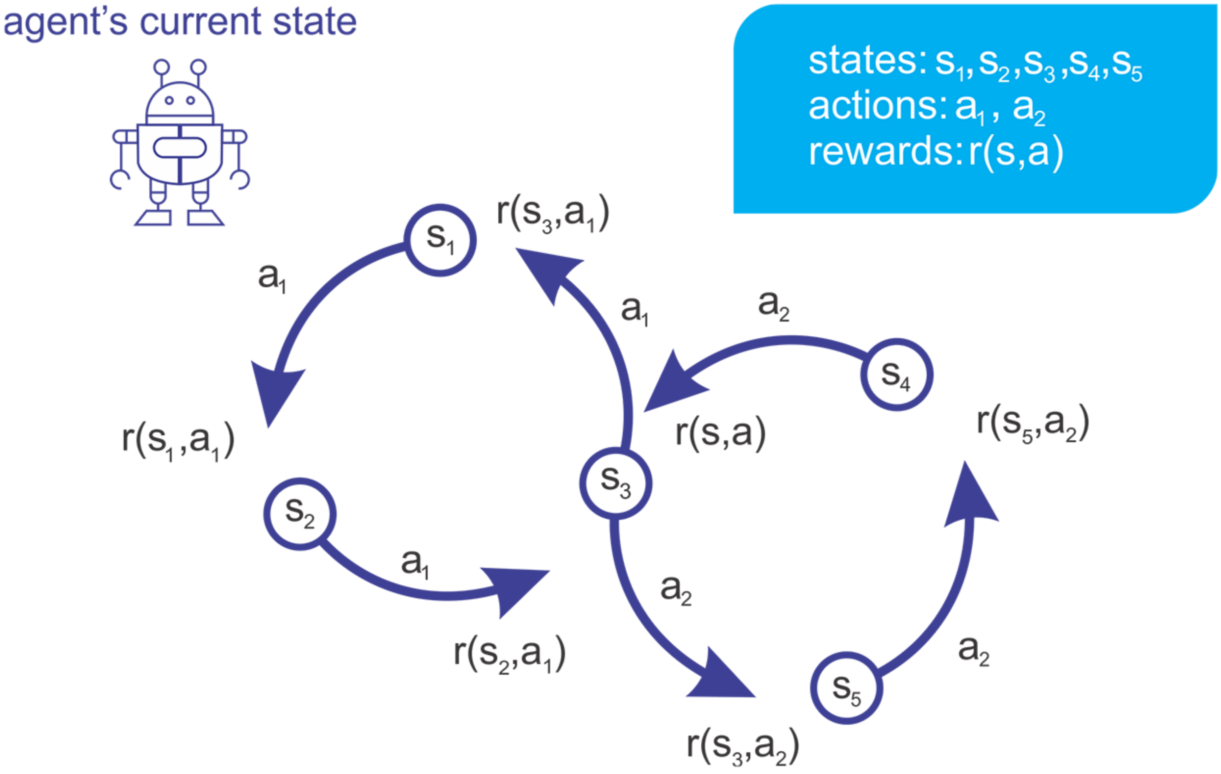

Dataset
Load DATA
Pre Process (OneHotEncodng, adding historical data to user)
Split Data (80:20)
Training set
Test set (split 50/50)
Construct the TF Model
Train Model
Normal
Cold Start
Trained Model
Remove historical data
Predicting buying event in a session
Retrieving item IDs purchased using predicted events


FM training loss per epoch
FM training loss per epoch
Training loss
0.55
0.50
0.45
0.40
0.35
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Epoch
FM validation loss per epoch
FM validation loss per epoch
Validation loss
0.60
0.59
0.58
0.57
0.56
0.55
0.54
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Epoch
NFM training loss per epoch
NFM training loss per epoch
Training loss
0.60
0.55
0.50
0.45
0.40
0.35
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Epoch
NFM validation loss per epoch
NFM validation loss per epoch
Validation loss
0.66
0.64
0.62
0.60
0.58
0.56
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Epoch

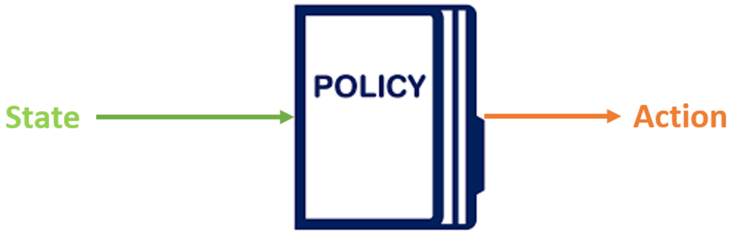

NFM test loss per epoch
NFM test loss per epoch
Test loss
0.66
0.64
0.62
0.60
0.58
0.56
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Epoch

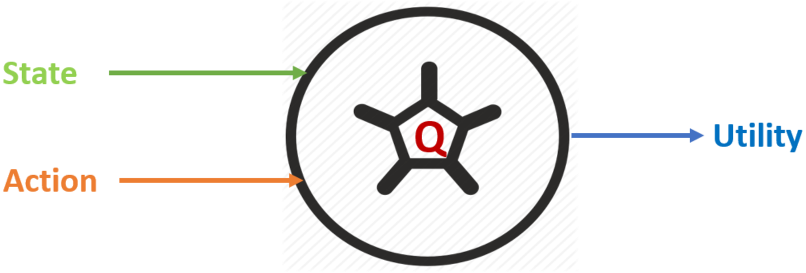
Chapter 11: Using Reinforcement Learning for Predictive Analytics

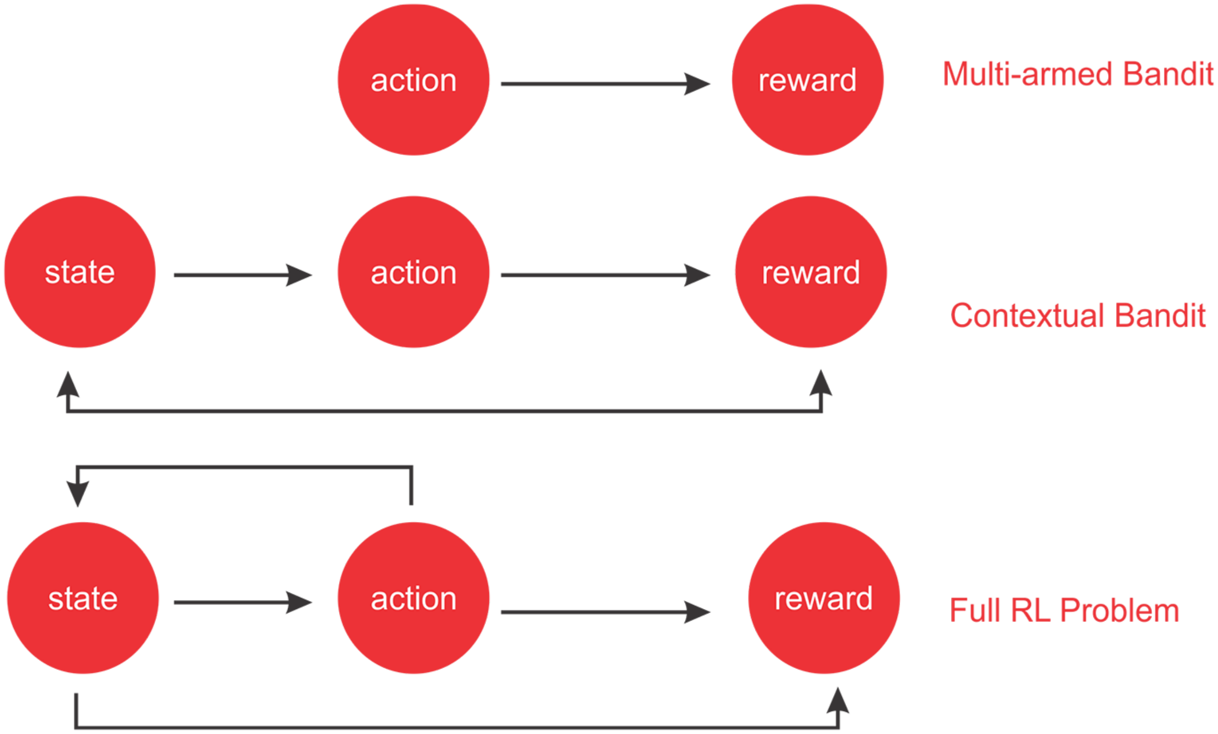


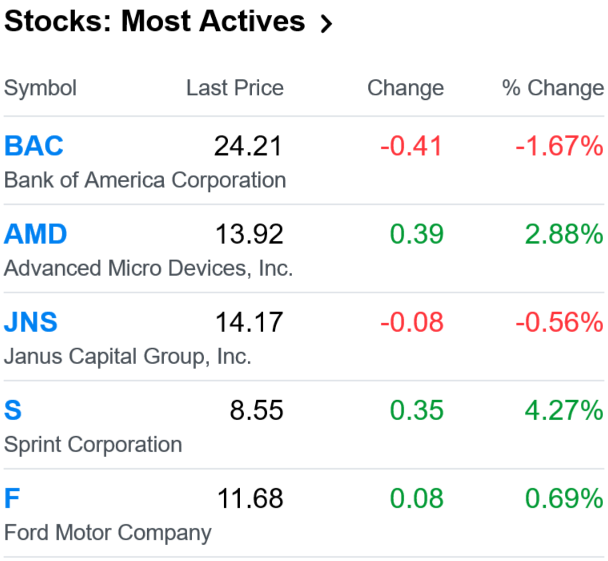


states: s_1, s_2, s_3, s_4, s_5
actions: a_1, a_2
rewards: $r(s,a)$



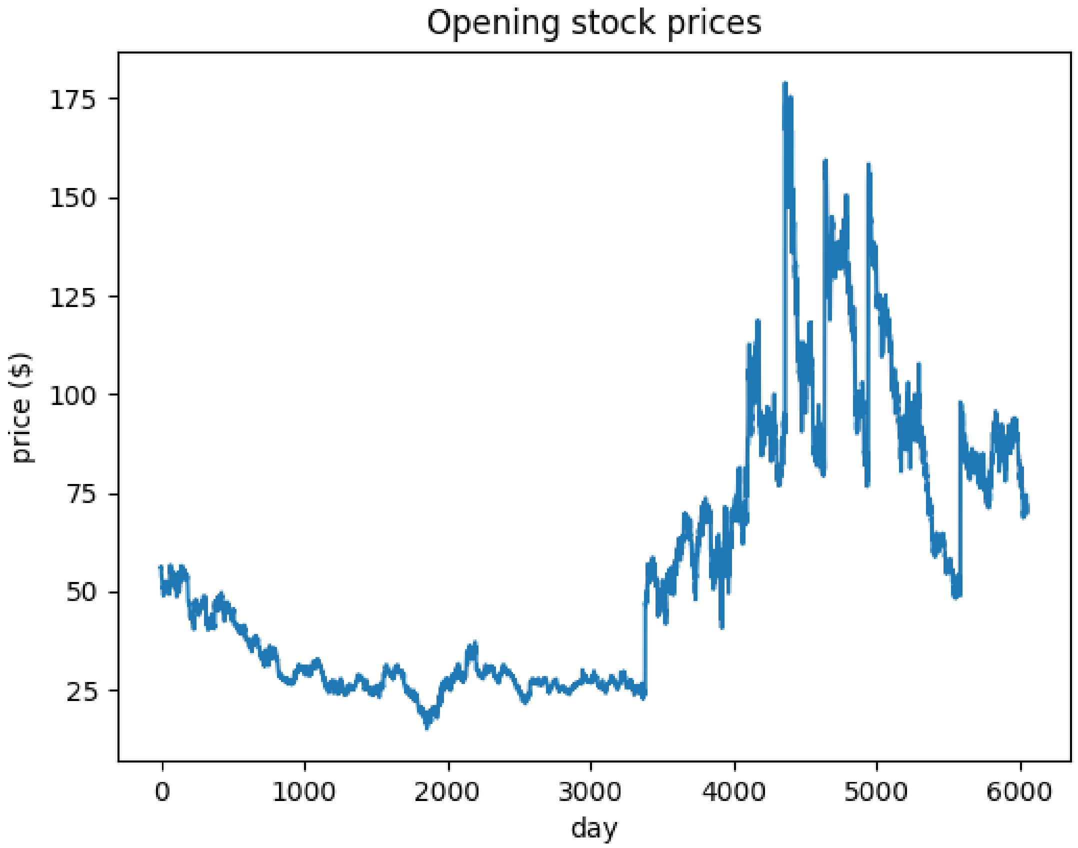


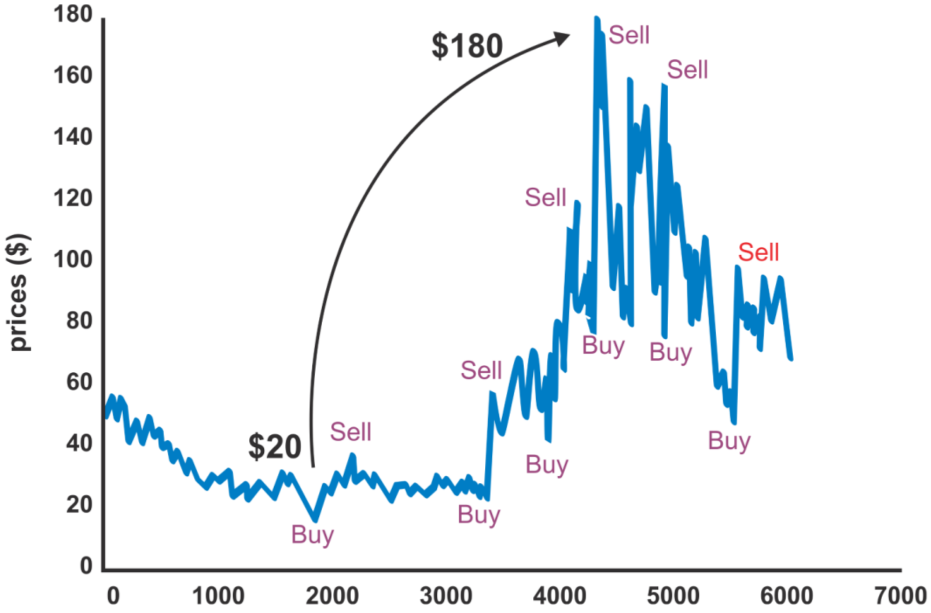




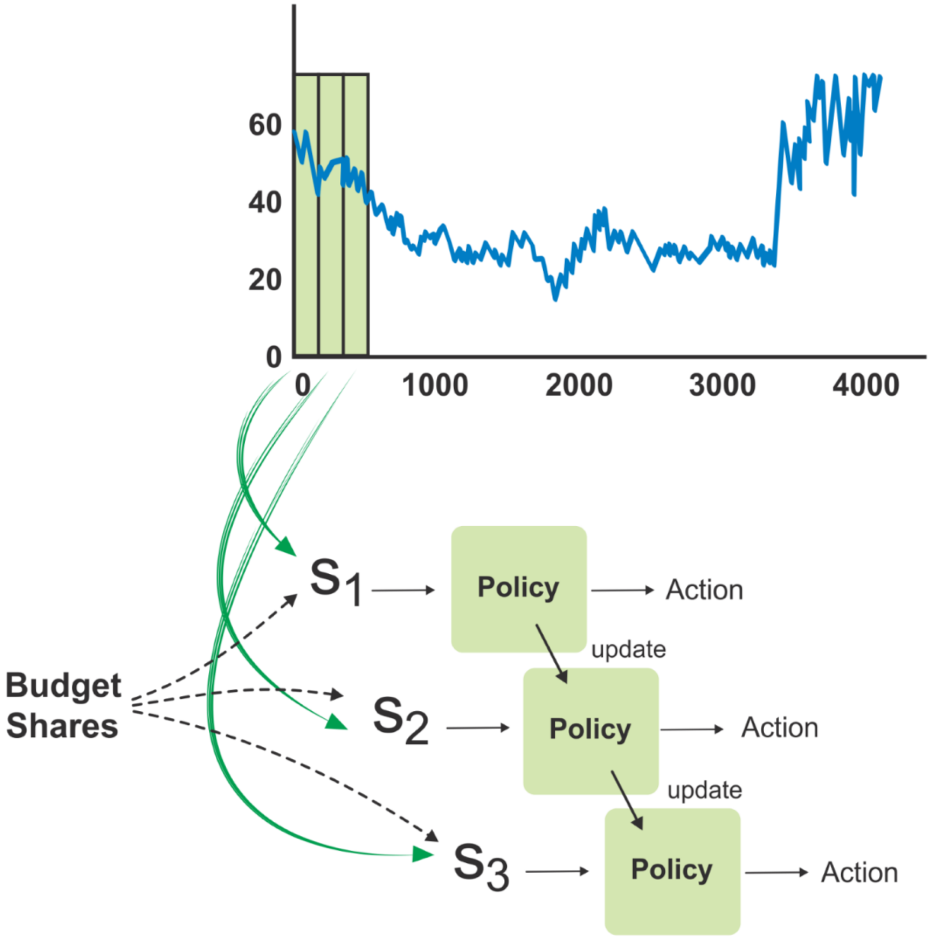
Stocks: Most Actives ›

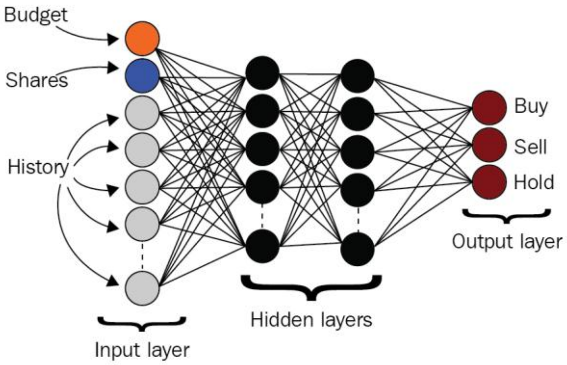
Symbol	Last Price	Change	% Change
BAC Bank of America Corporation	24.21	-0.41	-1.67%
AMD Advanced Micro Devices, Inc.	13.92	0.39	2.88%
JNS Janus Capital Group, Inc.	14.17	-0.08	-0.56%
S Sprint Corporation	8.55	0.35	4.27%
F Ford Motor Company	11.68	0.08	0.69%


Opening stock prices
price ($)
175
150
125
100
75
50
25
0
1000
2000
3000
4000
5000
6000
day



Infer(s)⇒ a
Do(s,a)⇒r, s'
Learn(s, r, a, s')


60
40
20
0
0
1000
2000
3000
4000
Budget
Shares
S_1
Policy
Action
update
S_2
Policy
Action
update
S_3
Policy
Action


Budget
Shares
History
Input layer
Hidden layers
Buy
Sell
Hold
Output layer