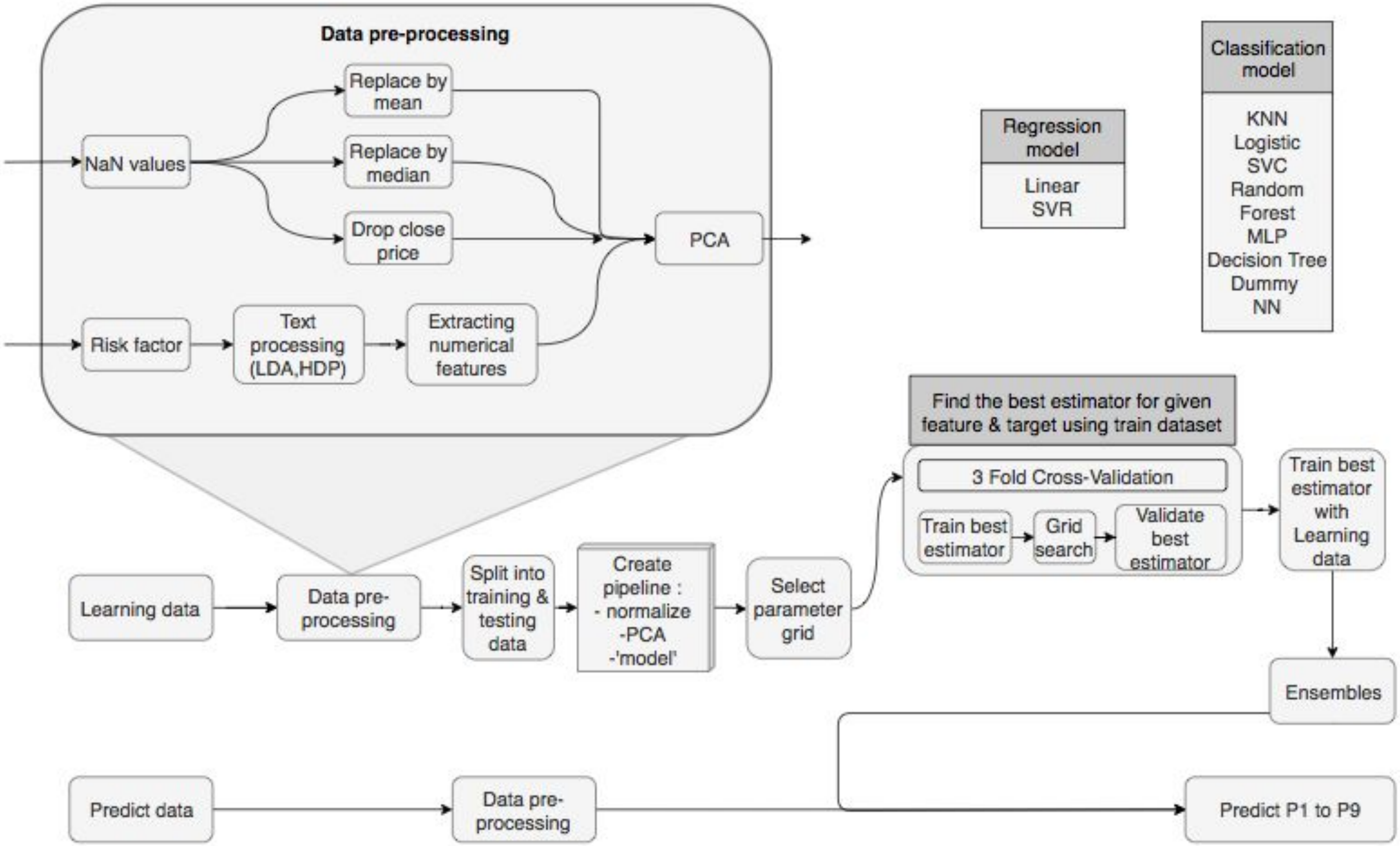
Data Science For Business

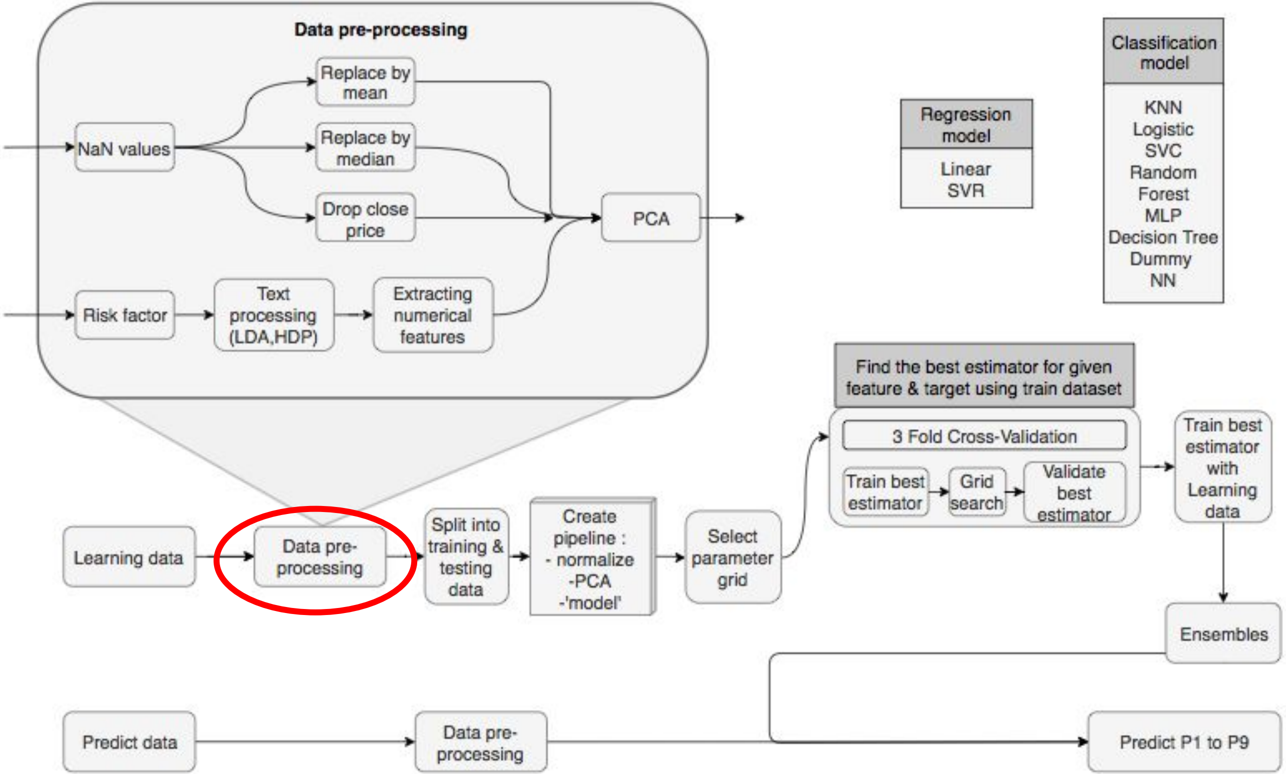
Learning to predict IPO performance... Data Science?

Claire Laurent, Devakumar Thammisetty, Cyprien Mercier

Prediction process : Overview

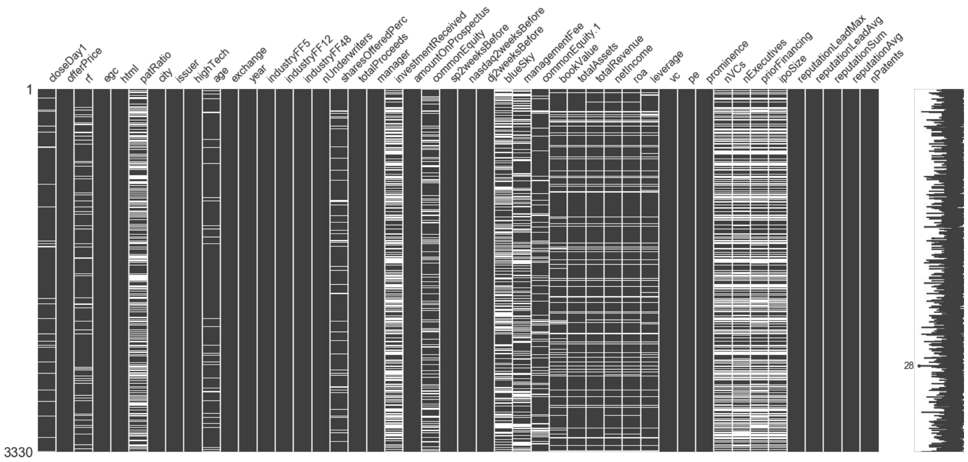


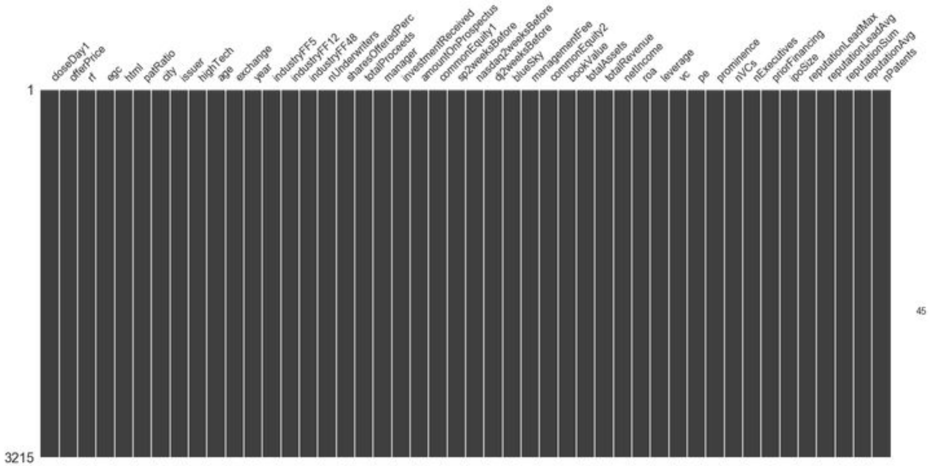
Data pre-processing



Processing of the data training set

- Use of Pandas profiling
- Determine missing data distribution and filling them in with the median or the mean:

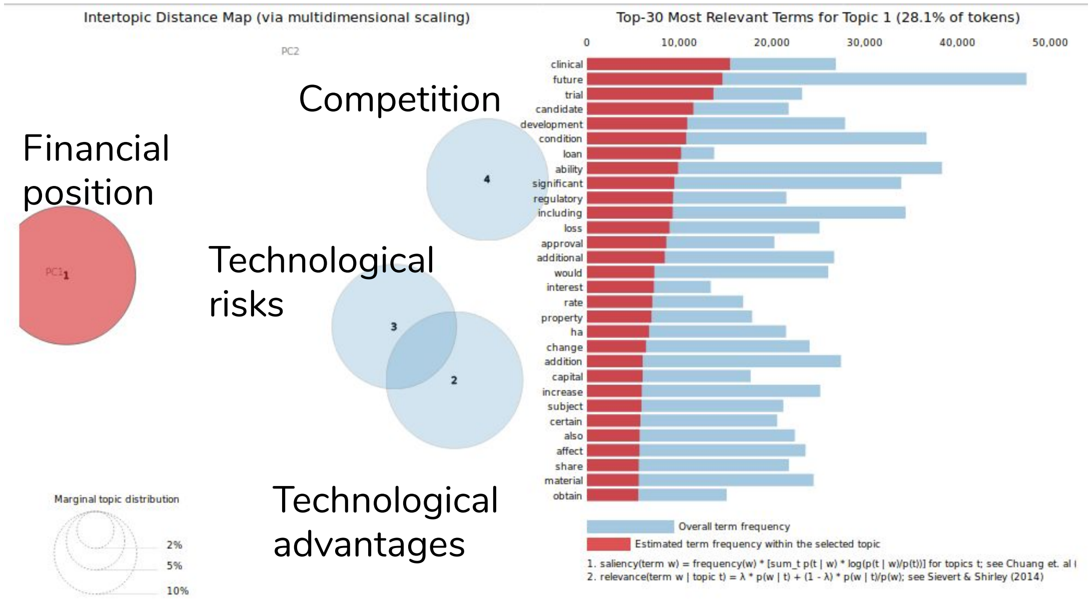


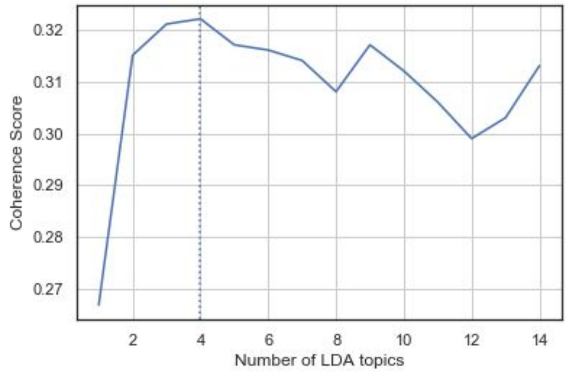


Given Learn data

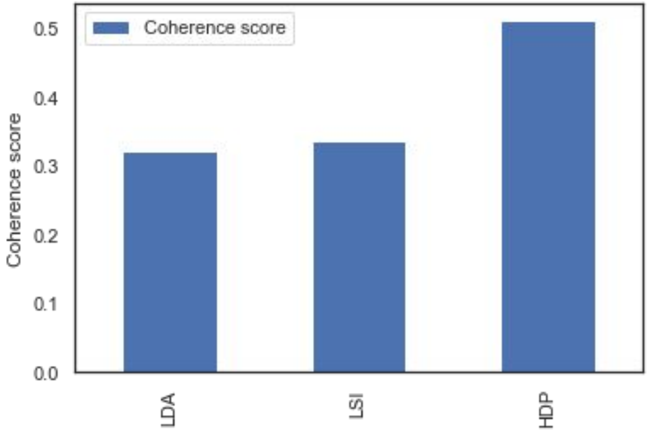
Learn data After pre-processing

Processing of the text data (LDA)



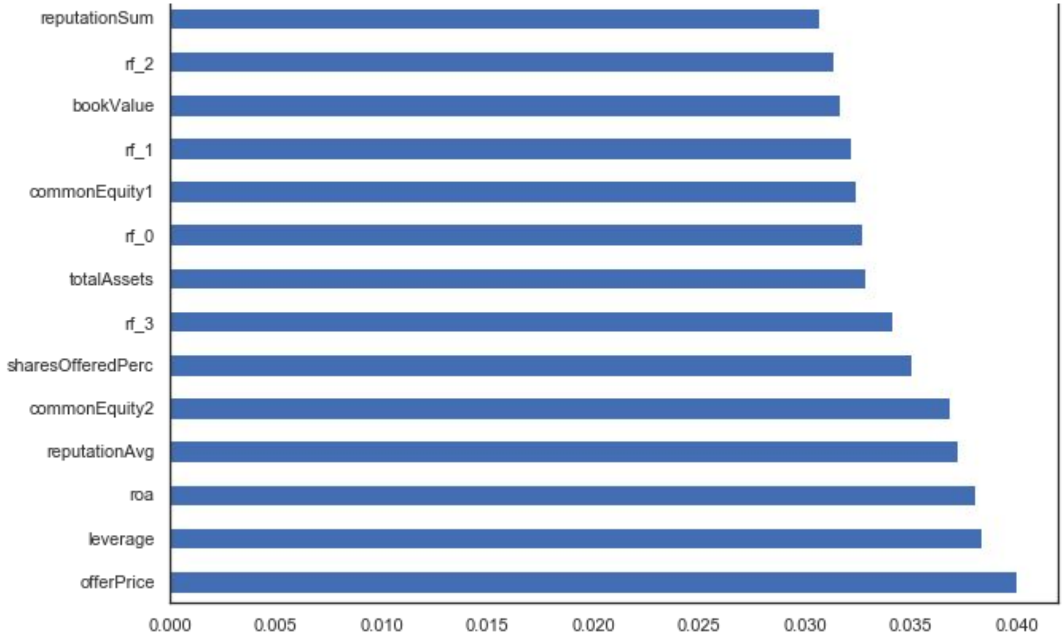


	LDA	LSI	HDP
Coherence score	0.321608	0.33685	0.511364

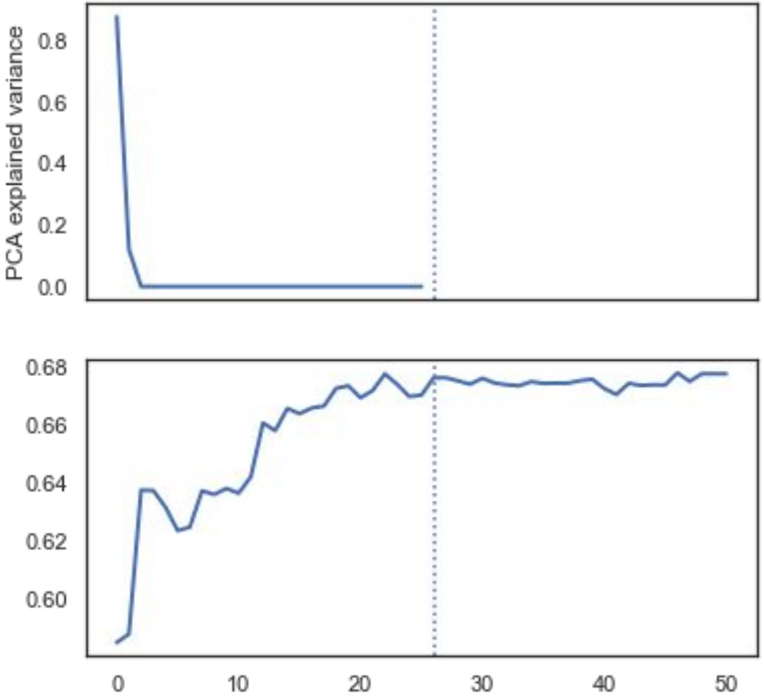


Data reduction and extraction of important features

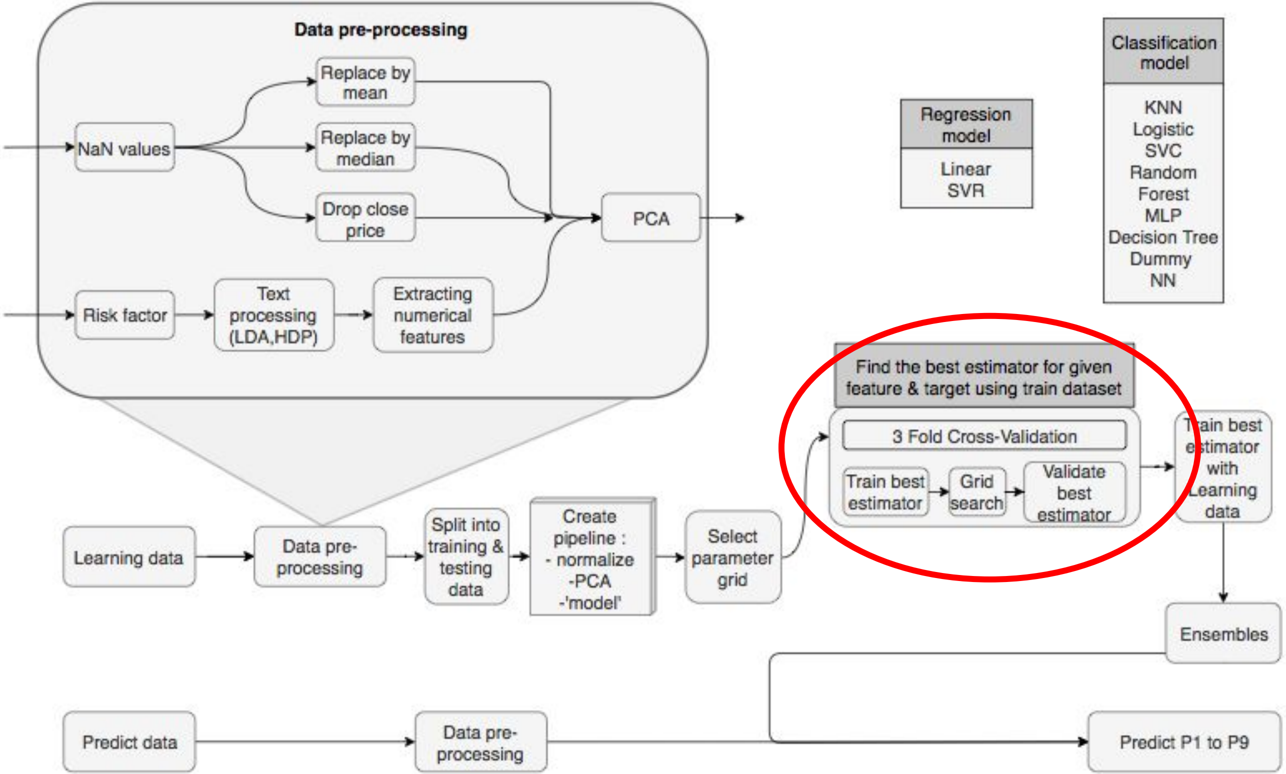
Features importance from Random Forests



PCA



Training - cross validation - selection of best estimator



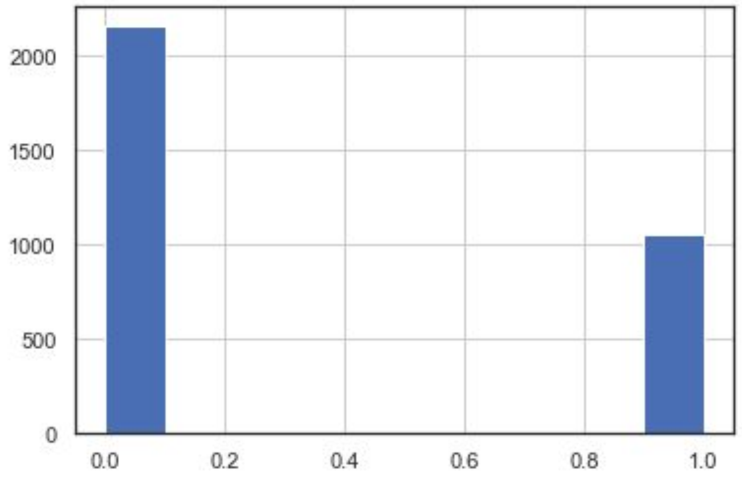
Process used for the predictions

Define X and Y	Define the models to try	Define best hyper-parameter	Validation	Test
For each prediction, either the predictors or the value to predict change. Define them for the 9 predictions	Have tried: - random - baseline - linear - logit (lasso) - decision tree - random forest - KNN - SVC - SVR - CNN	For **each** model: use Stratified Kfold and Grid search to determine the best hyper-parameters. Scoring metrics used: ROC, AUC, R2 and F1-score.	Draw the validation curve in order to check if the hyperparameters are good or not	Apply the model to the test set, compute metrics and compare models with each others.

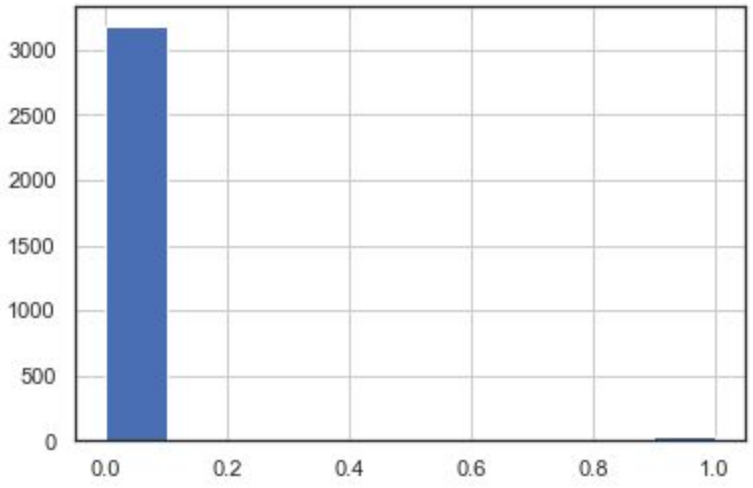
Do the steps for each model and decide which model to use for each prediction. Then use it to predict Y.

Scoring metrics - Selection

The price go up by more than 20%
(P4)

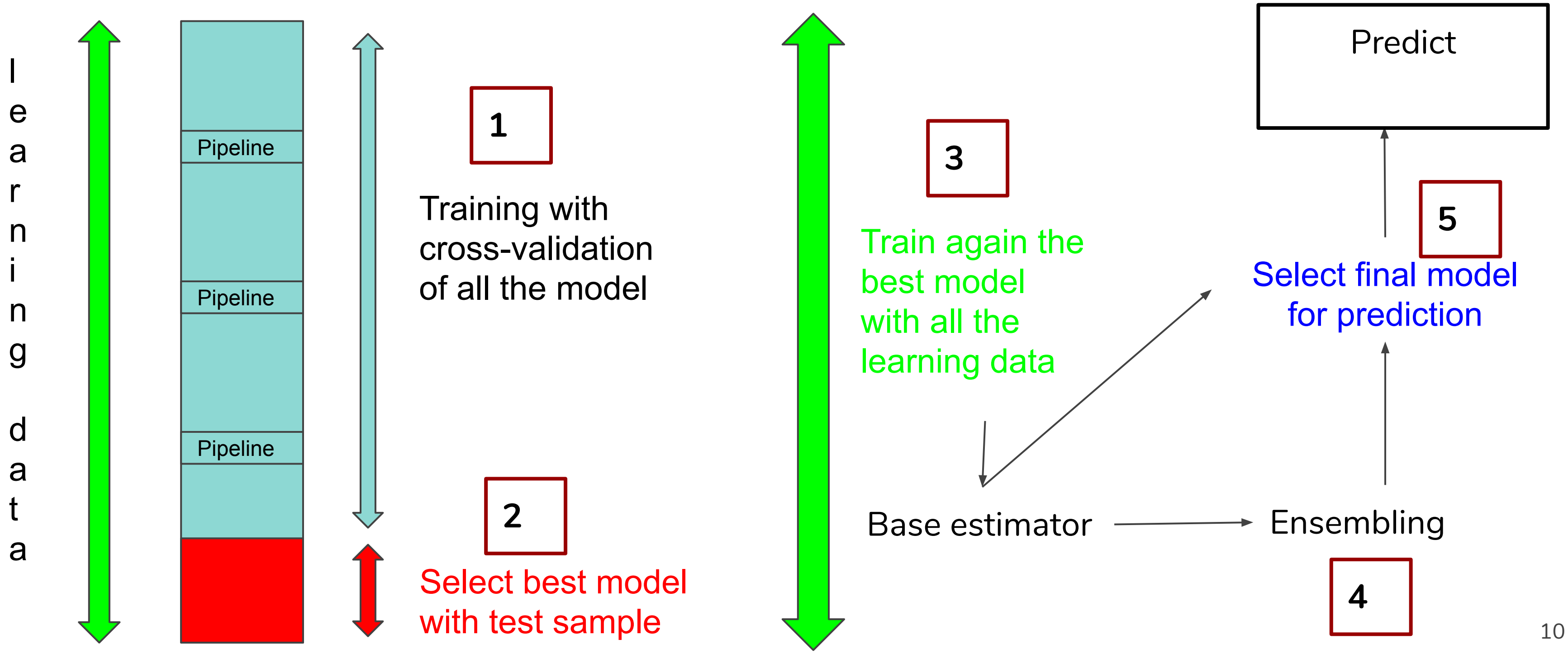


The price go down by more than 20%
(P5)



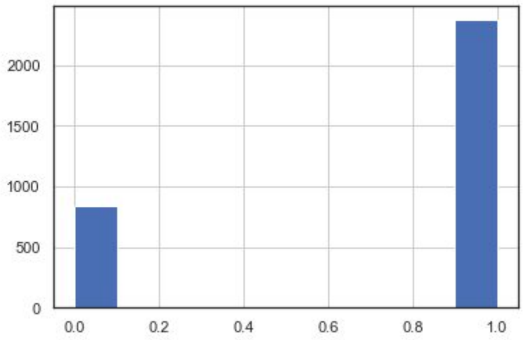
→ Two target variable distribution widely different, necessity of choosing the right metric (Accuracy will choose dummy classifier for P5)

Final prediction - Steps from best estimator



Best Model selection process: Example for P1

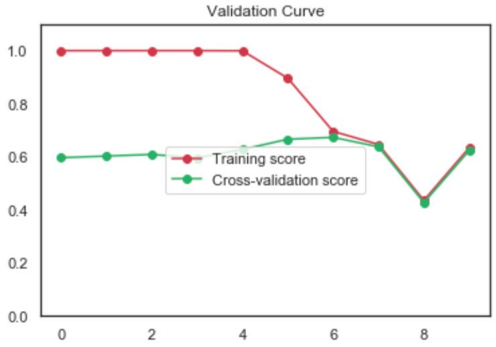
our objective:



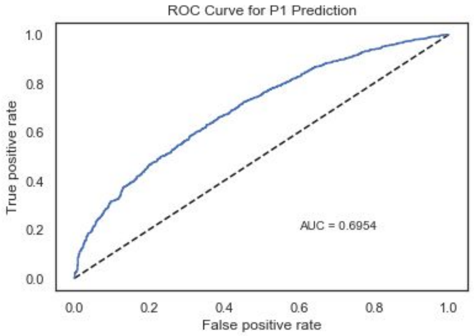
Hyper-parameter tuning

	roc_auc
MLPClassifier	0.673
LogisticRegression	0.670
RandomForestClassifier	0.670
KNeighborsClassifier	0.641
SVC	0.640
DecisionTreeClassifier	0.591
DummyClassifier	0.500
DummyClassifier-1	0.500

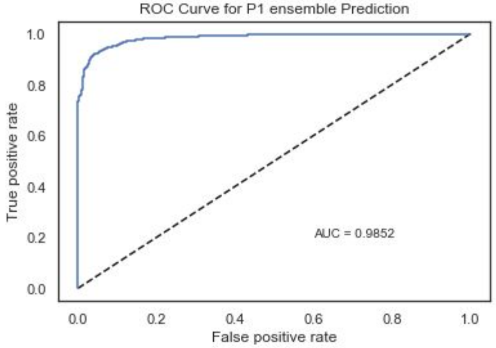
cross-validation curve :



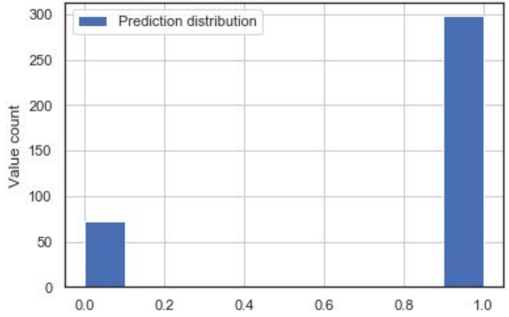
AUC with MLP classifier



Ensembles



Our Prediction



Our prediction - Selection of best estimators

Features	‘rf’	‘rf’	all	all	all	all	all	all	all
Targets	+/-	+/-	+/-	>20%	<-20%	$	$p^{>5\%}$	$p^{>50\%}$	$p^{<10\%}$
ROC-AUC score	P1	P2	P3	P4	P5	P6	P7	P8	P9
DecisionTreeClassifier	0.596	0.559	0.621	0.744	0.492	nan	-126	-126	-1.18e+03
DummyClassifier	0.5	0.5	0.5	0.5	0.5	nan	nan	nan	nan
DummyClassifier-1	0.5	0.5	0.5	0.5	0.5	nan	nan	nan	nan
KNeighborsClassifier	0.641	0.576	0.641	0.79	0.738	nan	-122	-122	-1.18e+03
LinearRegressor	nan	nan	nan	nan	nan	-0.524	nan	nan	nan
LogisticRegression	0.67	0.591	0.681	0.8	0.791	nan	-121	-121	-631
MLPClassifier	0.673	0.594	0.655	0.791	0.804	nan	-120	-121	-1.18e+03
RandomForestClassifier	0.643	0.569	0.646	0.788	0.716	nan	-124	-120	-1.17e+03
SVC	0.633	0.535	0.643	0.782	0.779	nan	-123	-122	-1.18e+03
SVR	nan	nan	nan	nan	nan	-0.341	nan	nan	nan

Conclusions

- ❑ Learned IPO processes and predicted various events using data science techniques.
- ❑ Built robust classifiers for various predictions and cross validated them on learn data, provided best possible predictions :).
- ❑ Obtained AUC as high as 0.8 to predict IPOs that give >20% profit. In addition, also obtained similar prediction capability for IPOs that go down by 20%.
- ❑ Improved performance with Ensembling
- ❑ Logistic regression, Random forests and Neural net based classifiers are found to give similar performance. However, Neural net based classifier turned out good for (4 of 9 predictions) followed by Logistic regression (3 out of 9).

Thank you

Our prediction using Heirarchical Dirichlet

Features	‘rf’	‘rf’	all	all	all	all	all	all	all
Targets	+/-	+/-	+/-	>20%	<-20%	$	$p^{>5\%}$	$p^{>50\%}$	$p^{<10\%}$
ROC-AUC score	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**
DecisionTreeClassifier	0.608	0.558	0.556	0.75	0.687	nan	-129	-129	-1.19e+03
DummyClassifier	0.5	0.5	0.5	0.5	0.5	nan	nan	nan	nan
DummyClassifier-1	0.5	0.5	0.5	0.5	0.5	nan	nan	nan	nan
KNeighborsClassifier	0.641	0.612	0.657	0.791	0.678	nan	-122	-122	-1.18e+03
LinearRegressor	nan	nan	nan	nan	nan	-0.521	nan	nan	nan
LogisticRegression	0.67	0.611	0.69	0.798	0.714	nan	-120	-121	-631
MLPClassifier	0.674	0.598	0.688	0.799	0.721	nan	-119	-120	-1.18e+03
RandomForestClassifier	0.665	0.623	0.636	0.784	0.739	nan	-124	-122	-1.17e+03
SVC	0.59	0.556	0.622	0.765	0.829	nan	-125	-124	-1.18e+03
SVR	nan	nan	nan	nan	nan	-0.0892	nan	nan	nan

Our prediction - F1 score

Features	‘rf’	‘rf’	all	all	all	all	all	all	all
Targets	+/-	+/-	+/-	>20%	<-20%	$	$p^{>5\%}$	$p^{>50\%}$	$p^{<10\%}$
F1 score	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**
DecisionTreeClassifier	0.84	0.84	0.84	0.485	0	nan	-126	-126	-1.17e+03
DummyClassifier	0.84	0.84	0.84	0.494	0.0185	nan	nan	nan	nan
DummyClassifier-1	0.84	0.84	0.84	0	0	nan	nan	nan	nan
KNeighborsClassifier	0.84	0.84	0.841	0.546	0	nan	-122	-122	-1.18e+03
LinearRegressor	nan	nan	nan	nan	nan	-0.522	nan	nan	nan
LogisticRegression	0.838	0.84	0.839	0.572	0	nan	-121	-121	-631
MLPClassifier	0.84	0.84	0.834	0.595	0	nan	-120	-120	-1.19e+03
RandomForestClassifier	0.827	0.791	0.819	0.552	0	nan	-122	-121	-1.18e+03
SVC	0.84	0.84	0.831	0.525	0	nan	-123	-123	-1.17e+03
SVR	nan	nan	nan	nan	nan	-0.348	nan	nan	nan

Back up

	P1	P2	P3	P4	P5	P6	P7	P8	P9
DecisionTreeClassifier	0.608	0.558	0.556	0.75	0.687	nan	-129	-129	-1.19e+03
DummyClassifier	0.5	0.5	0.5	0.5	0.5	nan	nan	nan	nan
DummyClassifier-1	0.5	0.5	0.5	0.5	0.5	nan	nan	nan	nan
KNeighborsClassifier	0.641	0.612	0.657	0.791	0.678	nan	-122	-122	-1.18e+03
LinearRegressor	nan	nan	nan	nan	nan	-0.521	nan	nan	nan
LogisticRegression	0.67	0.611	0.69	0.798	0.714	nan	-120	-121	-631
MLPClassifier	0.674	0.598	0.688	0.799	0.721	nan	-119	-120	-1.18e+03
RandomForestClassifier	0.665	0.623	0.636	0.784	0.739	nan	-124	-122	-1.17e+03
SVC	0.59	0.556	0.622	0.765	0.829	nan	-125	-124	-1.18e+03
SVR	nan	nan	nan	nan	nan	-0.0892	nan	nan	nan

Model vs Predictor

	P1	P2	P3	P4	P5	P6	P7	P8	P9
Logit									
Baseline									
Linear									
Knn									
SVC									
Decision Tree									
Random F									
SVR									
MLP									

Processing of the data training set

- drop columns with high cardinality (city and manager)
- decide to only use industryFF12: drop industryFF5 and industryFF48
- create dummy variables with industryFF12 and exchange
- create new variables:
  - **return** = closeDay1-offerPrice/OfferPrice
  - **raisingPrice** = 1 if return > 0 and 0 otherwise
- Processed text data inside rf field: remove punctuation, lemmatize the text, remove a custom list of stopwords
- Use LDA model to define topics and extract feature vector for each observation

Processing of the data to predict

Same process but don’t drop any lines

Profile report and observations

- Presence of missing values: we have to either drop or process the missing fields
- High correlation among 5 fields : we may decide to ignore them, drop them, or use PCA to reduce the dimensionality
- Different scales, ranging from 0 to 1e9: we need to normalize the data
- Missing outcome: offerPrice(3.5%) and closeDay1(3.5%). Since there is no outcome, it may not be useful to use this data, so we may drop the corresponding rows.
- Only 22% of the companies are marked as emerging growth companies so there may have a bias.
- Most of the companies are listed in NASDAQ(2368), followed by NYSE(895)
- Data is present from 1996 to 2018, there is more data in the late 90s, but data is well spread across years.
- Five fields are skewed (totalProceeds, InvestmentReceived, commonEquity1, totalRevenue, nPatents)
- 19 fields out of 47 have missing entries. Highest missing entries in investmentReceived(45%) followed by nExecutives, priorFinancing, nVCs, patRatio, managementFee(32.9%) in descending order

Profile report and observations

Dataset info

Number of variables	47
Number of observations	3330
Total Missing (%)	8.8%
Total size in memory	1.1 MiB
Average record size in memory	341.0 B

Variables types

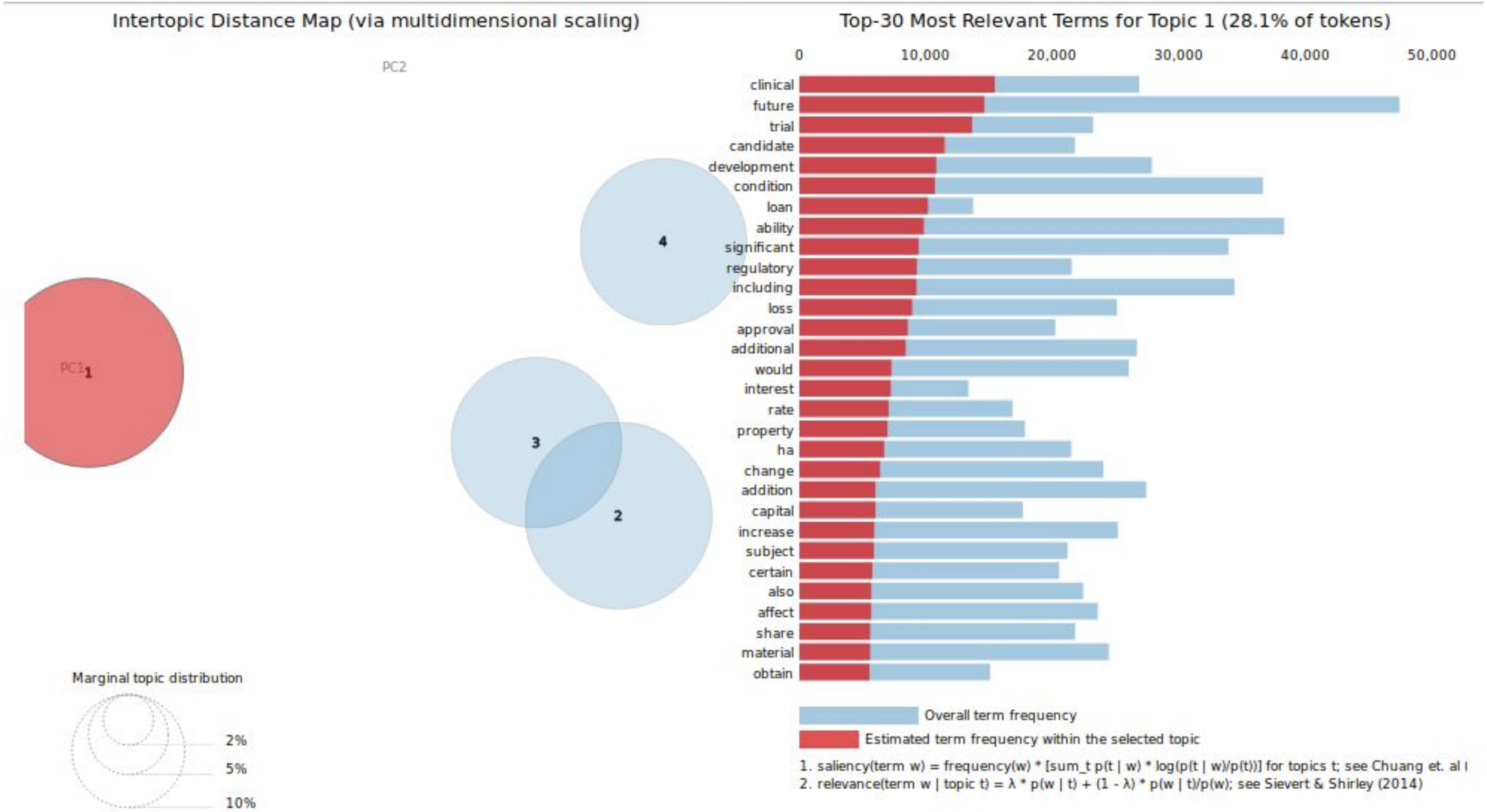
Numeric	28
Categorical	7
Boolean	6
Date	0
Text (Unique)	1
Rejected	5
Unsupported	0

Dataset info

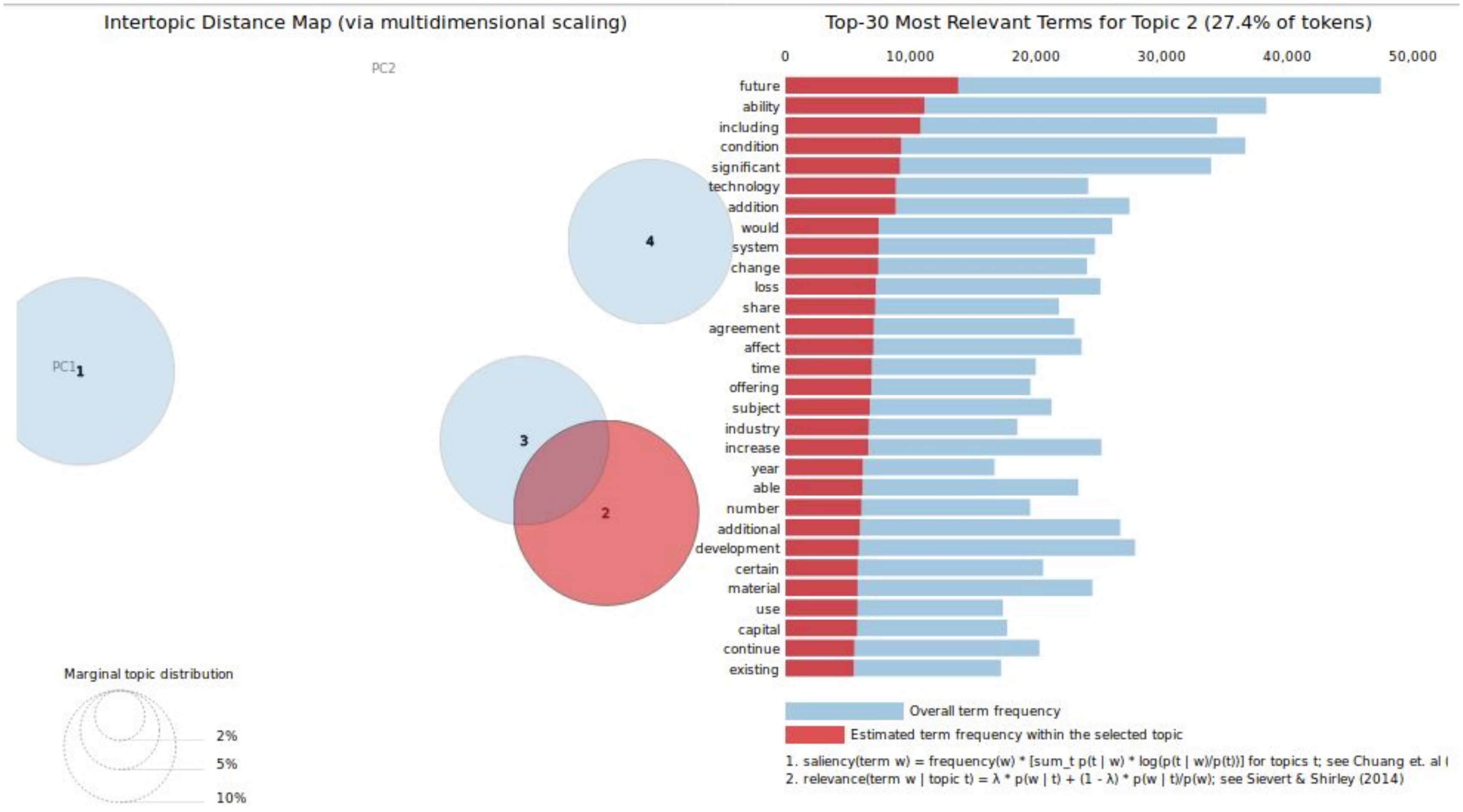
Number of variables	55
Number of observations	370
Total Missing (%)	22.7%
Total size in memory	146.5 KiB
Average record size in memory	405.3 B

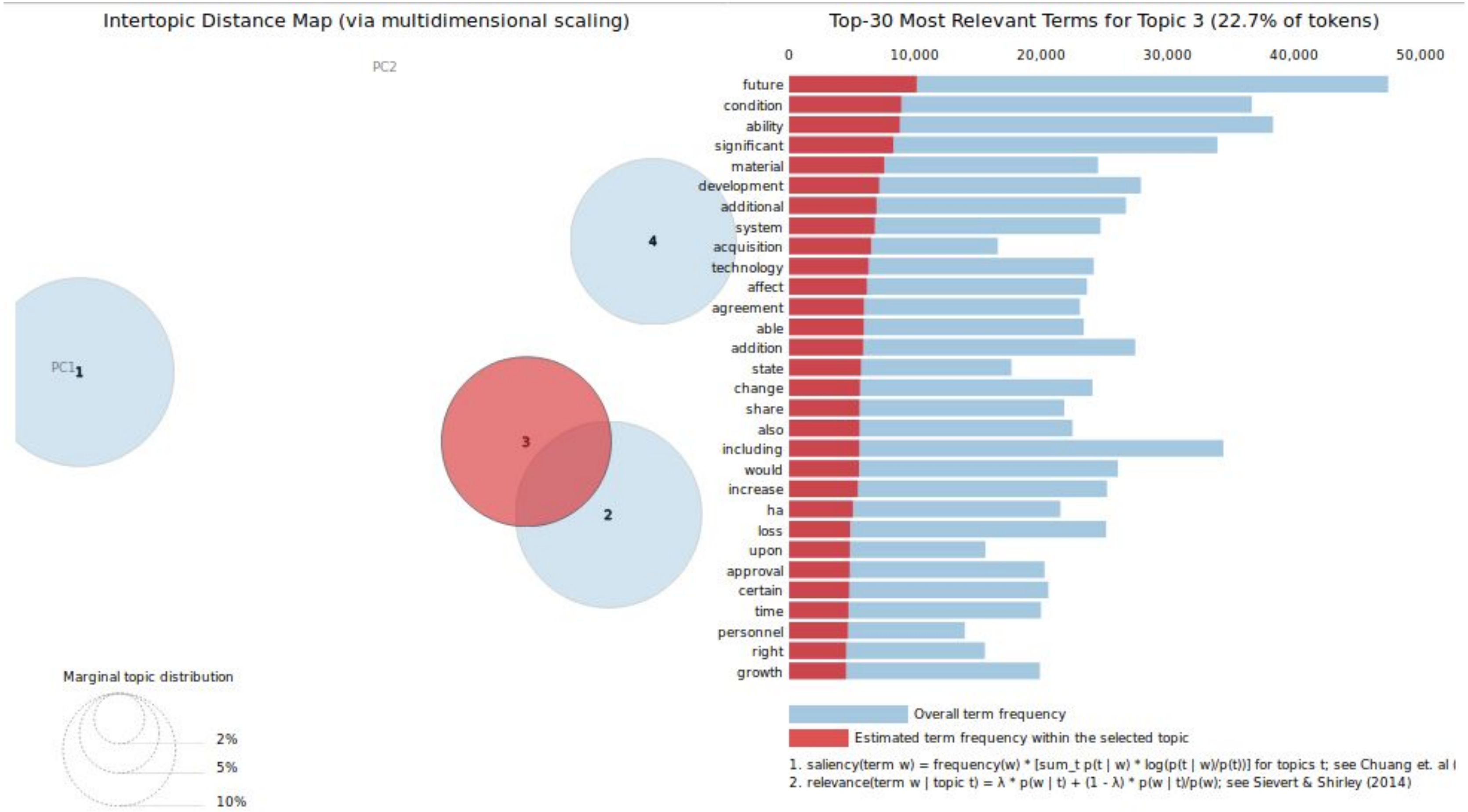
Variables types

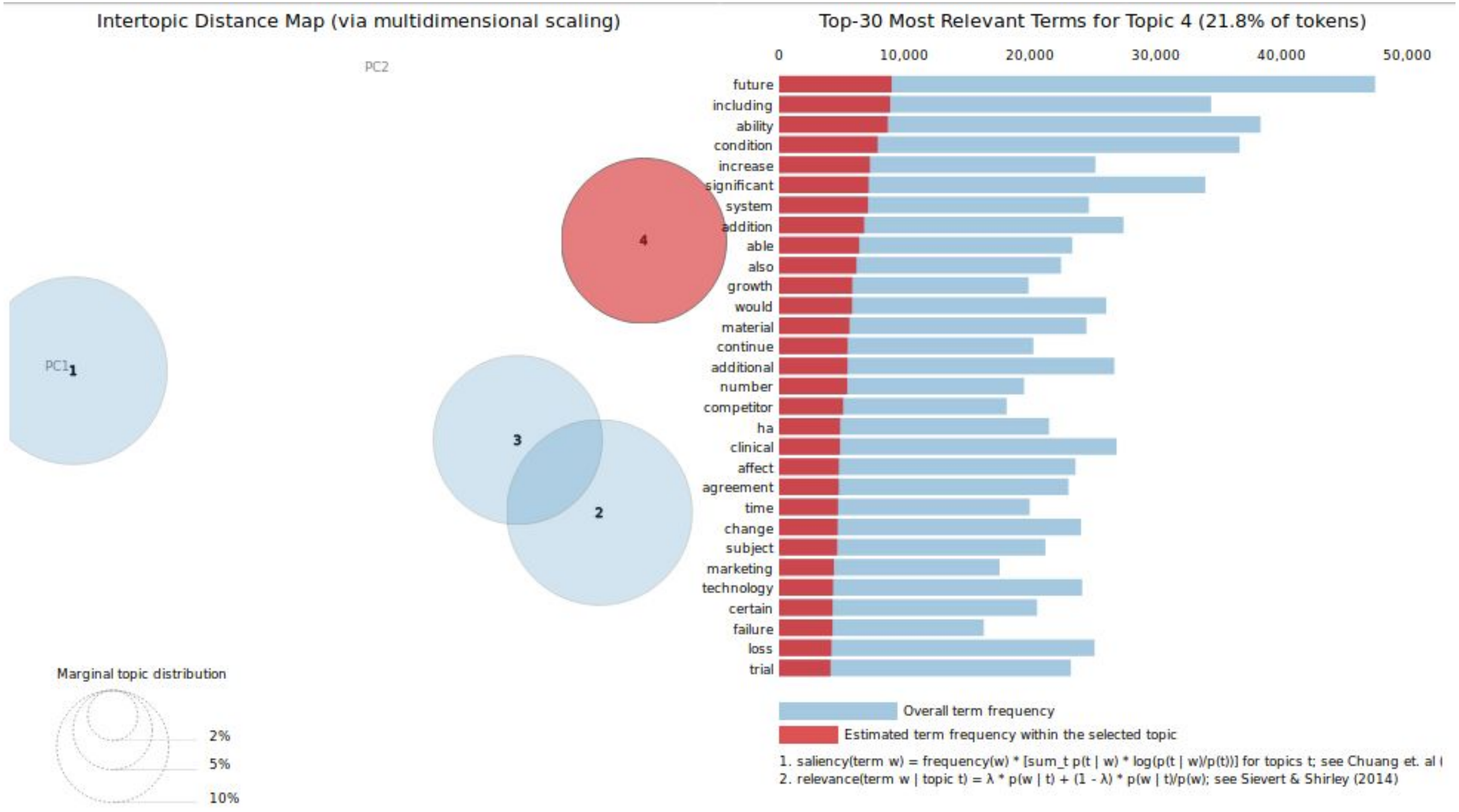
Numeric	24
Categorical	7
Boolean	6
Date	0
Text (Unique)	1
Rejected	17
Unsupported	0



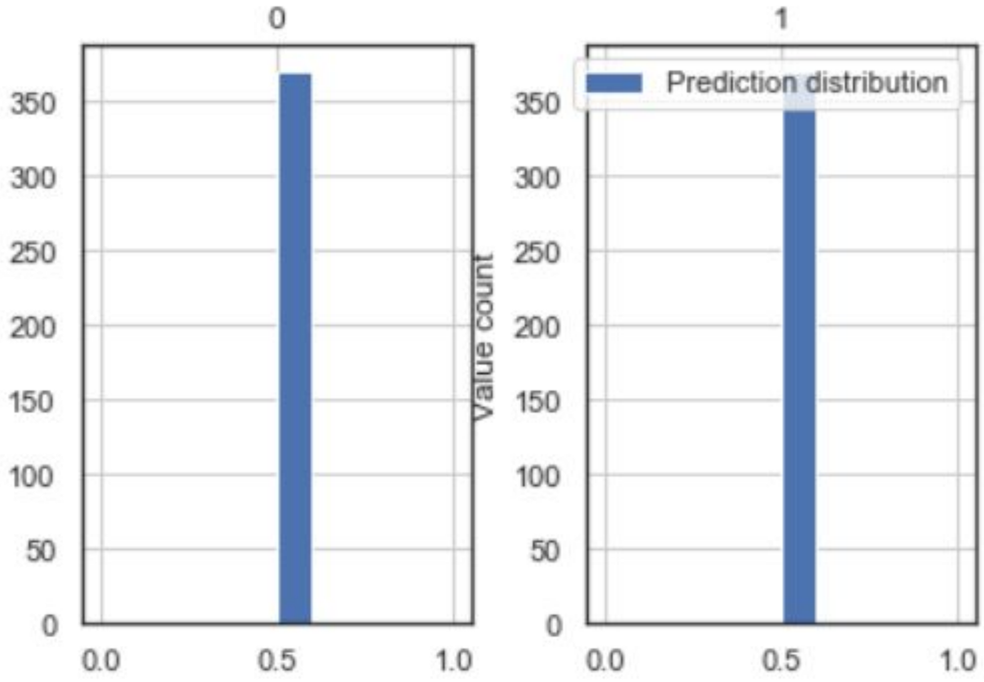
Intertopic Distance Map (via multidimensional scaling)
PC2
PC1
1
2
3
4
Marginal topic distribution
2%
5%
10%
Top-30 Most Relevant Terms for Topic 1 (28.1% of tokens)
0
10,000
20,000
30,000
40,000
50,000
clinical
future
trial
candidate
development
condition
loan
ability
significant
regulatory
including
loss
approval
additional
would
interest
rate
property
ha
change
addition
capital
increase
subject
certain
also
affect
share
material
obtain
Overall term frequency
Estimated term frequency within the selected topic
1. saliency(term w) = frequency(w) * [sum_t p(t | w) * log(p(t | w)/p(t))] for topics t; see Chuang et. al
2. relevance(term w | topic t) = λ * p(w | t) + (1 - λ) * p(w | t)/p(w); see Sievert & Shirley (2014)


Intertopic Distance Map (via multidimensional scaling)
PC2
PC1
1
2
3
4
Marginal topic distribution
2%
5%
10%
Top-30 Most Relevant Terms for Topic 2 (27.4% of tokens)
0
10,000
20,000
30,000
40,000
50,000
future
ability
including
condition
significant
technology
addition
would
system
change
loss
share
agreement
affect
time
offering
subject
industry
increase
year
able
number
additional
development
certain
material
use
capital
continue
existing
Overall term frequency
Estimated term frequency within the selected topic
1. saliency(term w) = frequency(w) * [sum_t p(t | w) * log(p(t | w)/p(t))] for topics t; see Chuang et. al (
2. relevance(term w | topic t) = λ * p(w | t) + (1 - λ) * p(w | t)/p(w); see Sievert & Shirley (2014)

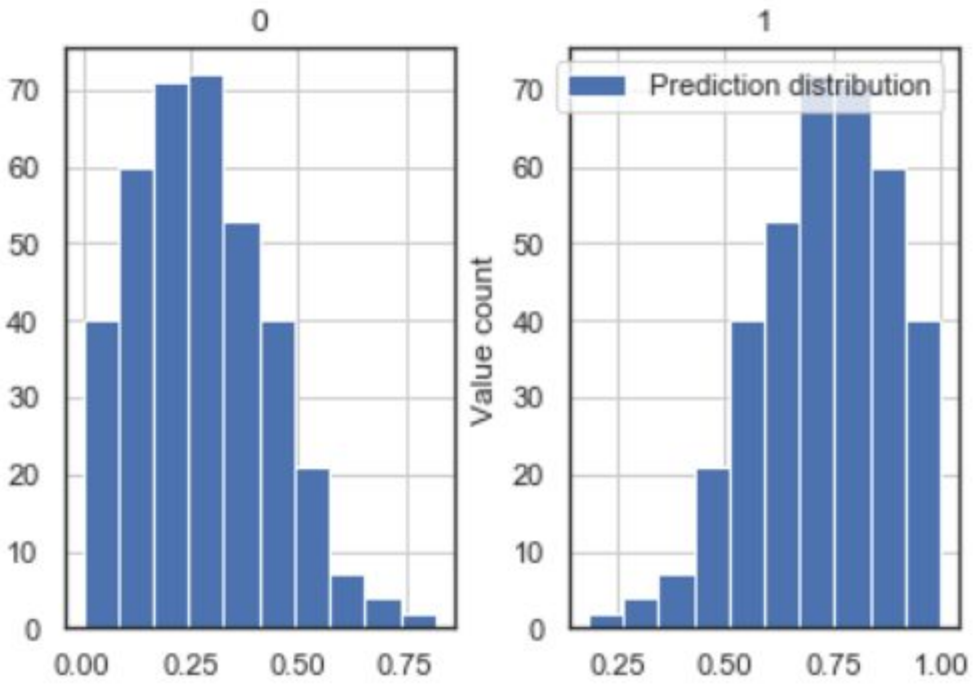

Intertopic Distance Map (via multidimensional scaling)
PC2
PC1
1
2
3
4
Marginal topic distribution
2%
5%
10%
Top-30 Most Relevant Terms for Topic 3 (22.7% of tokens)
0
10,000
20,000
30,000
40,000
50,000
future
condition
ability
significant
material
development
additional
system
acquisition
technology
affect
agreement
able
addition
state
change
share
also
including
would
increase
ha
loss
upon
approval
certain
time
personnel
right
growth
Overall term frequency
Estimated term frequency within the selected topic
1. saliency(term w) = frequency(w) * [sum_t p(t | w) * log(p(t | w)/p(t))] for topics t; see Chuang et. al (
2. relevance(term w | topic t) = λ * p(w | t) + (1 - λ) * p(w | t)/p(w); see Sievert & Shirley (2014)


Intertopic Distance Map (via multidimensional scaling)
PC2
PC1
1
2
3
4
Marginal topic distribution
2%
5%
10%
Top-30 Most Relevant Terms for Topic 4 (21.8% of tokens)
0
10,000
20,000
30,000
40,000
50,000
future
including
ability
condition
increase
significant
system
addition
able
also
growth
would
material
continue
additional
number
competitor
ha
clinical
affect
agreement
time
change
subject
marketing
technology
certain
failure
loss
trial
Overall term frequency
Estimated term frequency within the selected topic
1. saliency(term w) = frequency(w) * [sum_t p(t | w) * log(p(t | w)/p(t))] for topics t; see Chuang et. al
2. relevance(term w | topic t) = λ * p(w | t) + (1 - λ) * p(w | t)/p(w); see Sievert & Shirley (2014)

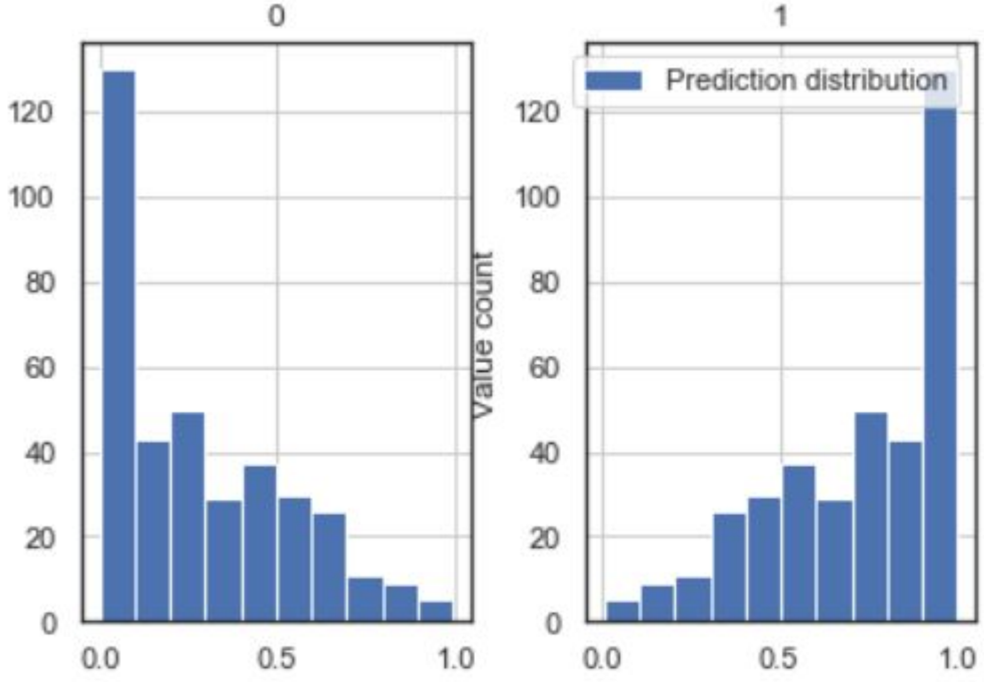
P9


0
1
Prediction distribution
Value count
350
300
250
200
150
100
50
0
0.0
0.5
1.0

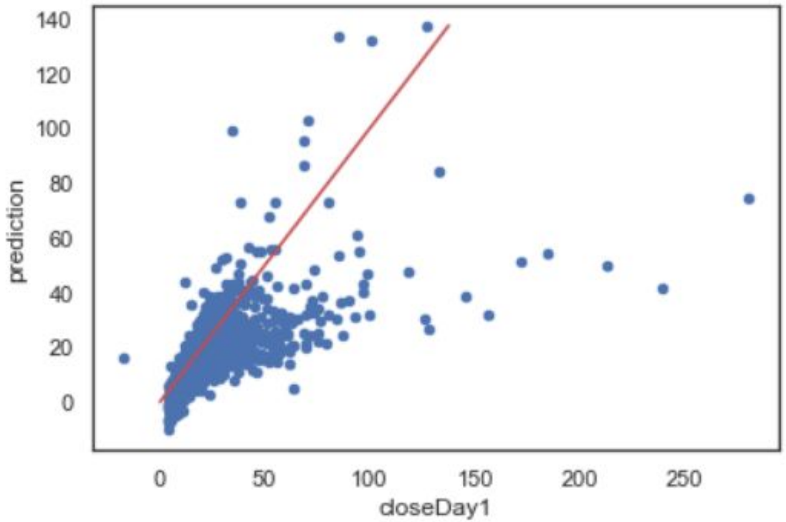
P8


0
1
Prediction distribution
Value count
0
10
20
30
40
50
60
70
0.00
0.25
0.50
0.75
1.00

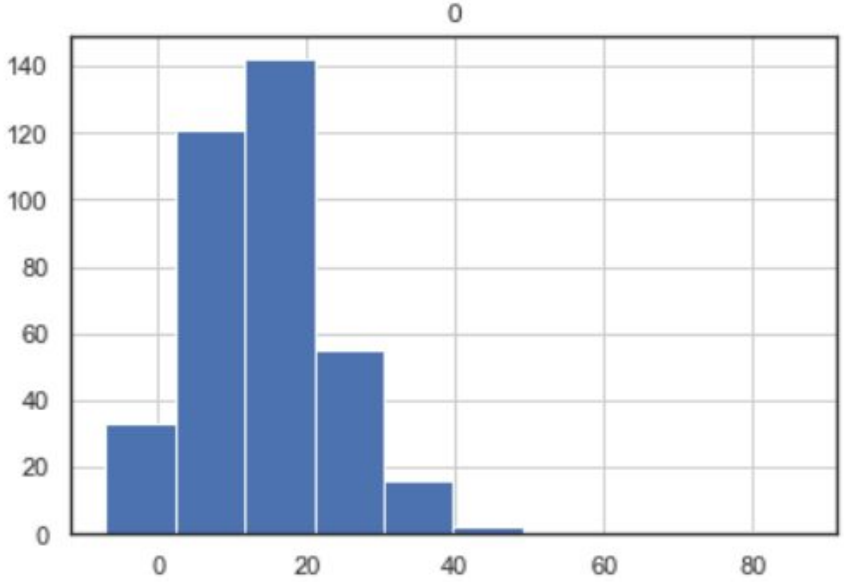
```
Using bagging classifier for P7 ...
```



P6

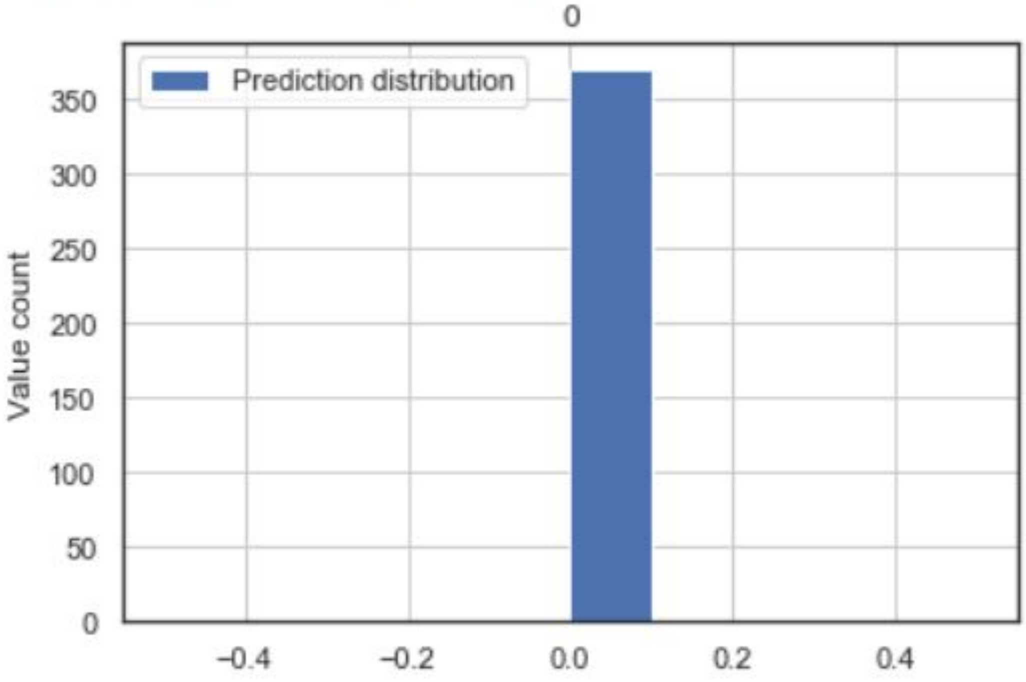


prediction
closeDay1
0
50
100
150
200
250
140
120
100
80
60
40
20
0

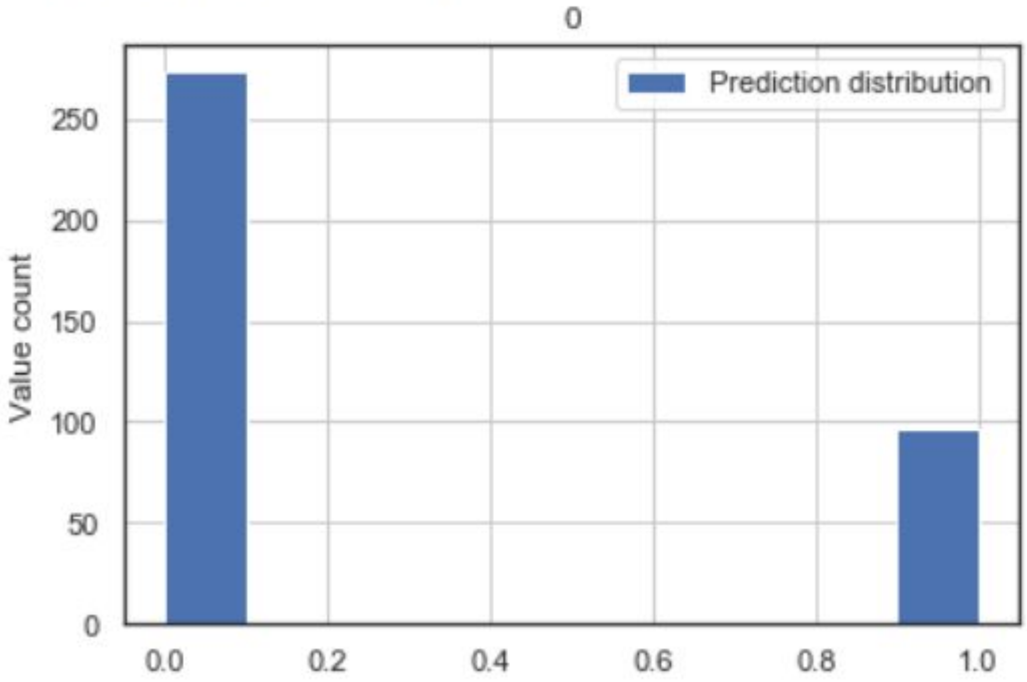


0
140
120
100
80
60
40
20
0
0
20
40
60
80

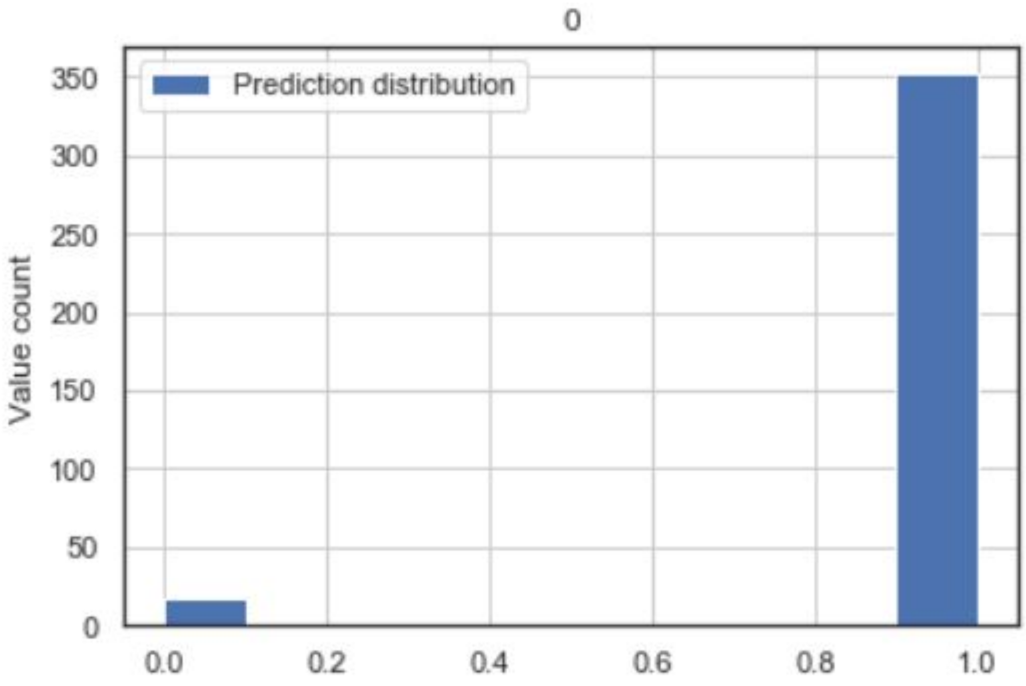
```
Using bagging classifier for P5 ...
```



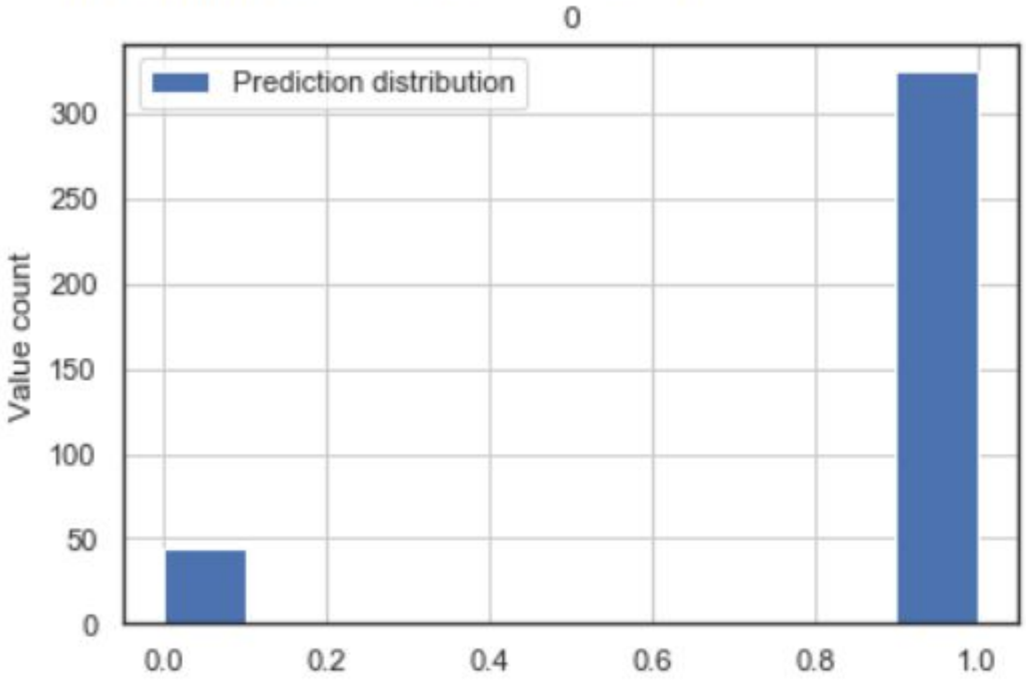
```
Using bagging classifier for P4 ...
```



P3


0
Prediction distribution
Value count
350
300
250
200
150
100
50
0
0.0
0.2
0.4
0.6
0.8
1.0

```
Using bagging classifier for P2 ...
```



Using bagging classifier for P1 ...