Presentation online:
https://alvinrindra.github.io/impress/ginkgo-analytics/data-case

Notebook online:
https://www.kaggle.com/alvinrindra/data-case-ai-solution-from-consumer-narrative

Data Case:
AI Solution for Helpdesk Inc.

Data Case Talk:
Alvin Rindra Fazrie
alvinrindra@gmail.com

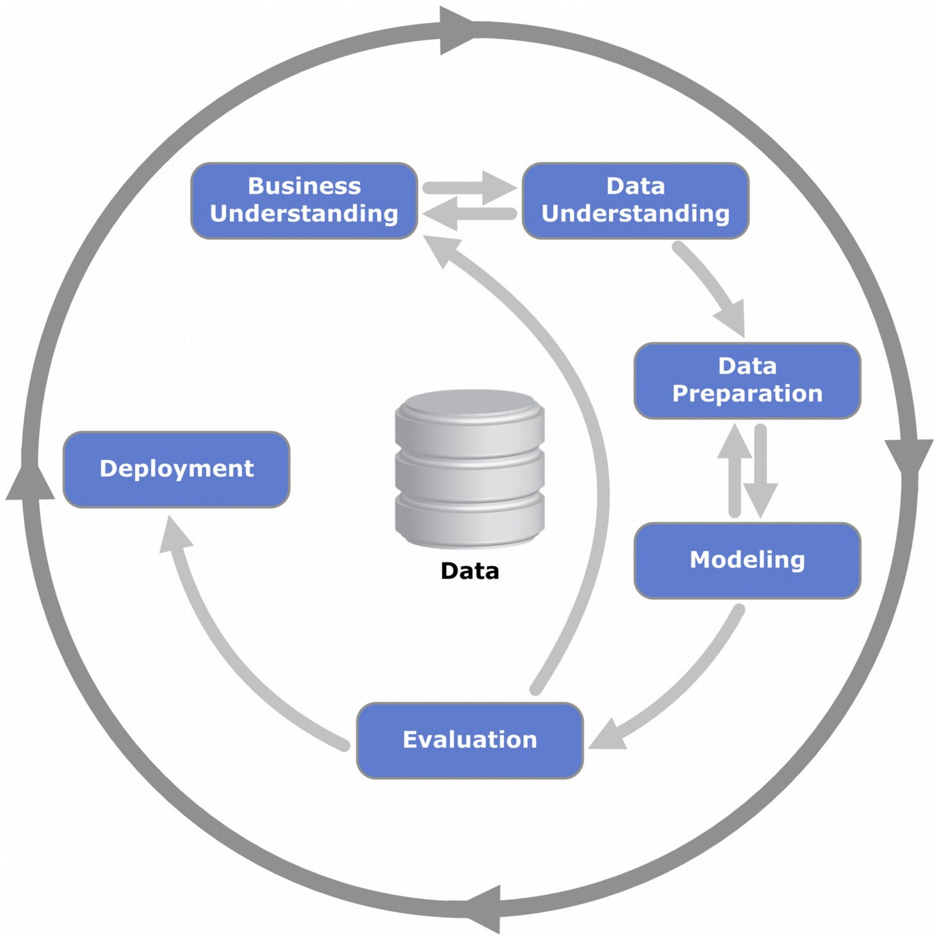
Business Case

The web contains more and more user genereated data. One huge source of such information can be found in the myriads of customer written complaints and reviews.

The aim of this data challenge is to show that there is value in this unstructured text data. Can you convince the C-Suite of Helpdesk Inc. a helpdesk and support company that there is value in working with the unstructured text data in their tickets and support request by applying state-of-the-art deep learning models? In a first meeeting you want to convince them, that a neural net can learn to distinguish between the relevant topics and problems talked about in a customer complaint.

Is it possible to train a neural net which can be used to predict the Product or Issue category? Feel free to focus on the categories with the highest impact. Another helpful information would be an accurate prediction if a complaint is resolved in a timely manner and if the consumer will dispute the decision. Depending on that prediction, tickets with a high probability of disputes or late resolves could be handled with specialized processes.

CRISP-DM Methodology



Business Understanding

- **Task:**

  To convince the C-Suite of Helpdesk Inc. to apply state-of-the-art deep learning models to solve the problems from unstructured text data.

- **Plan:**

  To enable a simpler ticket submission system which does not have the consumer to click through a complicated form and fill several fields.

- **Analytic Approach:**

  Multi-class Classification for the Product Classifier and Binary Classification for the Consumer Dispute Classifier

Data Understanding

- **Data Collection**
- **Exploratory Data Analysis**

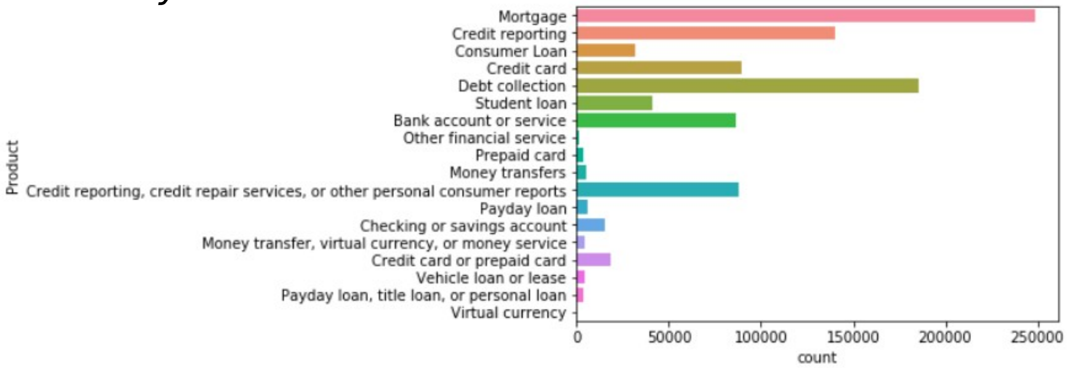
```python
# Data Collection
df = pd.read_csv('../input/Consumer_Complaints.csv')
print(df.shape)
df.head()
```

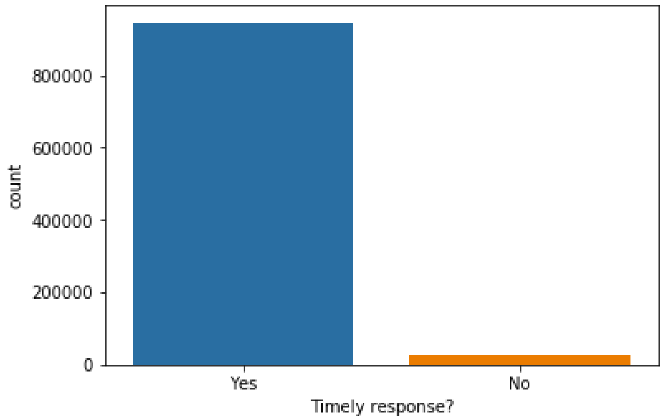
```
(972147, 18)
```

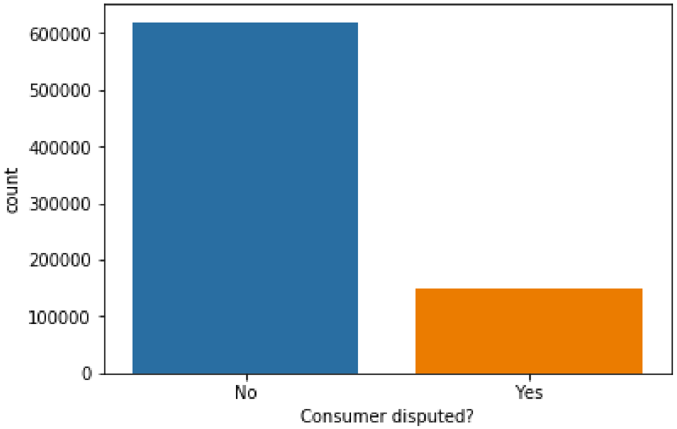
	Date received	Product	Sub-product	Issue	Sub-issue	Consumer complaint narrative	Company public response	Company	State	ZIP code	Tags	Consumer consent provided?	Submitted via	Date sent to company	Company response to consumer	Timely response?	Consumer disputed?	Complaint ID
0	03/12/2014	Mortgage	Other mortgage	Loan modification,collection,foreclosure	NaN	NaN	NaN	M&T BANK CORPORATION	MI	48382	NaN	NaN	Referral	03/17/2014	Closed with explanation	Yes	No	759217
1	10/01/2016	Credit reporting	NaN	Incorrect information on credit report	Account status	I have outdated information on my credit repor...	Company has responded to the consumer and the ...	TRANSUNION INTERMEDIATE HOLDINGS, INC.	AL	352XX	NaN	Consent provided	Web	10/05/2016	Closed with explanation	Yes	No	2141773
2	10/17/2016	Consumer Loan	Vehicle loan	Managing the loan or lease	NaN	I purchased a new car on XXXX XXXX. The car de...	NaN	CITIZENS FINANCIAL GROUP, INC.	PA	177XX	Older American	Consent provided	Web	10/20/2016	Closed with explanation	Yes	No	2163100
3	06/08/2014	Credit card	NaN	Bankruptcy	NaN	NaN	NaN	AMERICAN EXPRESS COMPANY	ID	83854	Older American	NaN	Web	06/10/2014	Closed with explanation	Yes	Yes	885638
4	09/13/2014	Debt collection	Credit card	Communication tactics	Frequent or repeated calls	NaN	NaN	CITIBANK, N.A.	VA	23233	NaN	NaN	Web	09/13/2014	Closed with explanation	Yes	Yes	1027760

Exploratory Data Analysis

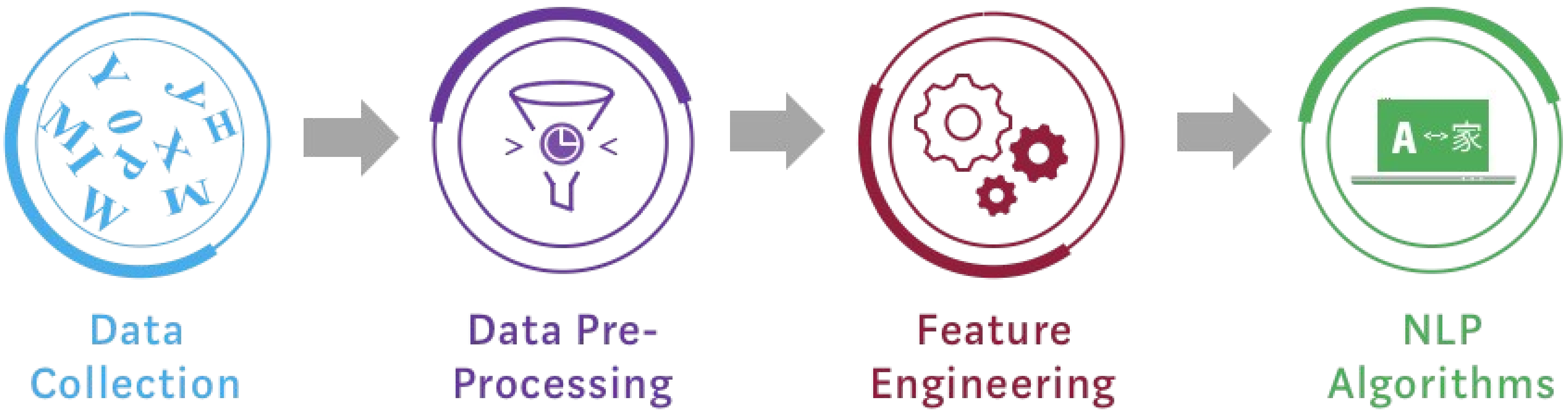
„EDA can never be the whole story, but nothing else can serve as the foundation stone“
- John Tukey







NLP Process Flow



Data Preprocessing

Better Data > Better Model

Data processing involves the following steps:

- Label Selection
- Remove NA values in every observation

- NLP and Regex Approaches:
    - Remove numeric and empty texts
    - Remove punctuation from texts
    - Convert words to lower case
    - Remove stop words
    - Remove unnecessary words
    - Stemming

Other approaches: Tokenization, Lemmatization, POS tagging

Data Preprocessing

Word Cloud as Narrative Visualization:

Data Preprocessing

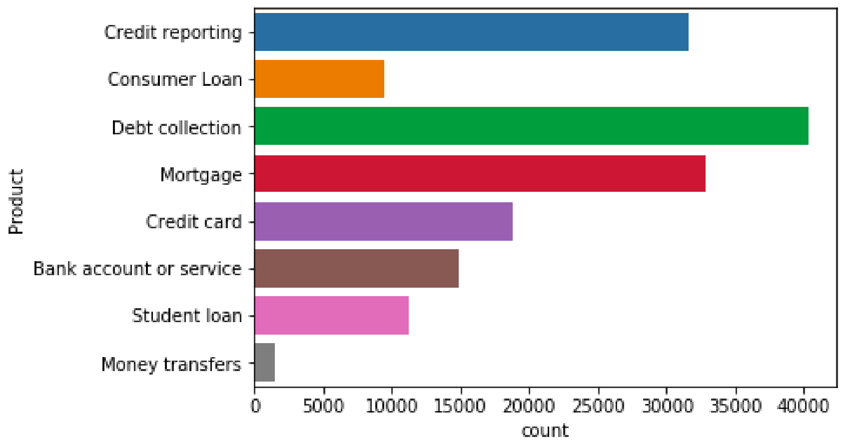
sel_df_cat['Consumer complaint narrative'][2]

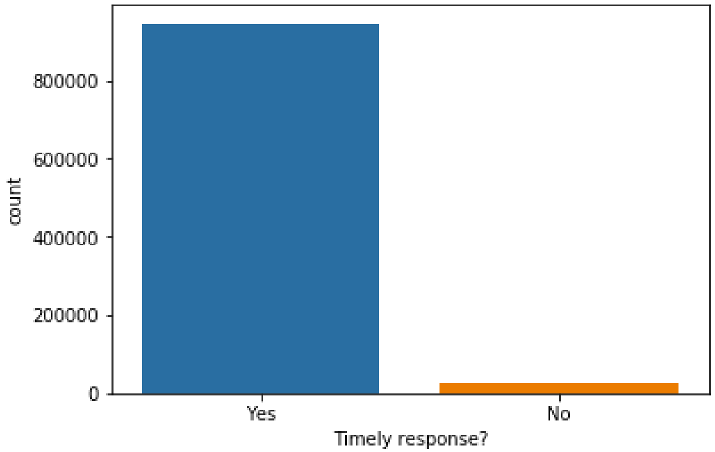
```
"I purchased a new car on XXXX XXXX. The car dealer called Citizens Bank to get a 10 day payoff on my loan, good till XXXX XXXX. The dealer sent the check the next day. When I balanced my checkbook on XXXX XXXX. I noticed that Citizens bank had taken the automatic payment out of my checking account at XXXX XXXX XXXX Bank. I called Citizens and they stated that they did not close the loan until XXXX XXXX. ( stating that they did not receive the check until XXXX. XXXX. ). I told them that I did not believe that the check took that long to arrive. XXXX told me a check was issued to me for the amount overpaid, they deducted additional interest. Today ( XXXX XXXX, ) I called Citizens Bank again and talked to a supervisor named XXXX, because on XXXX XXXX. I received a letter that the loan had been paid in full ( dated XXXX, XXXX ) but no refund check was included. XXXX stated that they hold any over payment for 10 business days after the loan was satisfied and that my check would be mailed out on Wed. the XX/XX/XXXX.. I questioned her about the delay in posting the dealer payment and she first stated that sometimes it takes 3 or 4 business days to post, then she said they did not receive the check till XXXX XXXX I again told her that I did not believe this and asked where is my money. She then stated that they hold the over payment for 10 business days. I asked her why, and she simply said that is their policy. I asked her if I would receive interest on my money and she stated no. I believe that Citizens bank is deliberately delaying the posting of payment and the return of consumer 's money to make additional interest for the bank. If this is not illegal it should be, it does hurt the consumer and is not ethical. My amount of money lost is minimal but if they are doing this on thousands of car loans a month, then the additional interest earned for them could be staggering. I still have another car loan from Citizens Bank and I am afraid when I trade that car in another year I will run into the same problem again."
```

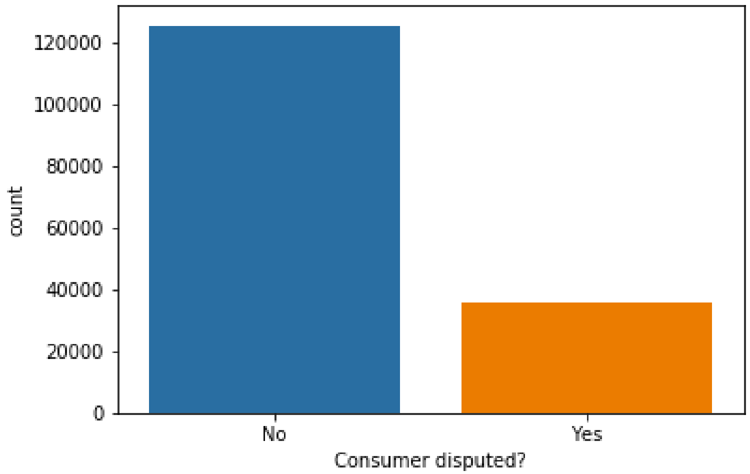
X[2]

```
'purchas new car car dealer call citizen bank get day payoff loan good till dealer sent check next day balanc checkbook notic citizen bank taken automat payment check account bank call citizen state close loan state receiv check told believ check took long arriv told check issu amount overpaid deduct addit interest today call citizen bank talk supervisor name receiv letter loan paid full date refund check includ state hold payment busi day loan satisfi check would mail wed question delay post dealer payment first state sometim take busi day post said receiv check till told believ ask money state hold payment busi day ask whi simpli said polici ask would receiv interest money state no believ citizen bank deliber delay post payment return consum money make addit interest bank illeg be hurt consum ethic amount money lost minim thousand car loan month addit interest earn could stagger still anoth car loan citizen bank afraid trade car anoth year run problem again'
```

Data Preprocessing

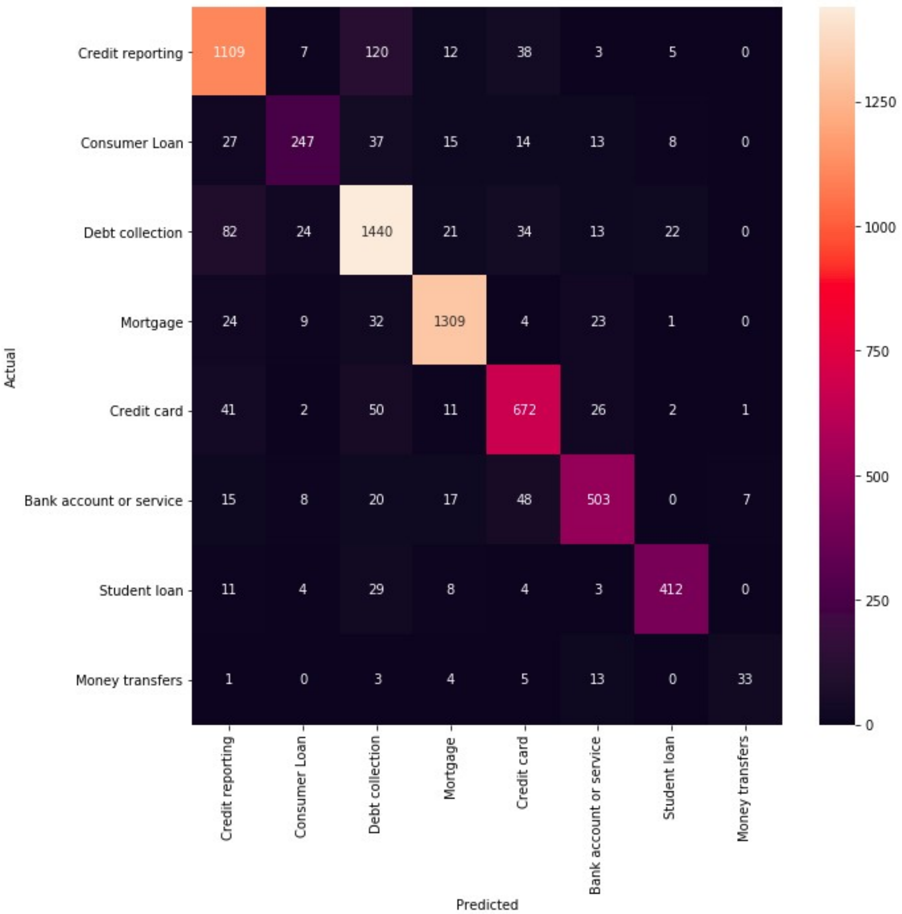






Intermezzo:

Classification Matrix for choosing training labels



	precision	recall	f1-score	support
Credit reporting	0.85	0.86	0.85	1294
Consumer Loan	0.82	0.68	0.75	361
Debt collection	0.83	0.88	0.86	1636
Mortgage	0.94	0.93	0.94	1402
Credit card	0.82	0.83	0.83	805
Bank account or service	0.84	0.81	0.83	618
Student loan	0.92	0.87	0.89	471
Money transfers	0.80	0.56	0.66	59
micro avg	0.86	0.86	0.86	6646
macro avg	0.85	0.80	0.82	6646
weighted avg	0.86	0.86	0.86	6646

Intermezzo:

Dealing with imbalanced classes

- TfidfVectorizer
- Finding unigrams and bigrams with chi2

```
# 'Bank account or service':
  . Most correlated unigrams:
. overdraft
. deposit
  . Most correlated bigrams:
. overdraft fee
. check account
# 'Consumer Loan':
  . Most correlated unigrams:
. vehicl
. car
  . Most correlated bigrams:
. car loan
. auto loan
# 'Credit card':
  . Most correlated unigrams:
. reward
. card
  . Most correlated bigrams:
. american express
. credit card
```

```
# 'Credit reporting':
  . Most correlated unigrams:
. experian
. equifax
  . Most correlated bigrams:
. tran union
. credit report
# 'Debt collection':
  . Most correlated unigrams:
. collect
. debt
  . Most correlated bigrams:
. collect debt
. collect agenc
# 'Money transfers':
  . Most correlated unigrams:
. moneygram
. western
  . Most correlated bigrams:
. money transfer
. western union
```

```
# 'Mortgage':
  . Most correlated unigrams:
. modif
. mortgag
  . Most correlated bigrams:
. mortgag payment
. loan modif
# 'Student loan':
  . Most correlated unigrams:
. student
. navient
  . Most correlated bigrams:
. privat loan
. student loan
```

Intermezzo:

Multinominal NB with limited data, nrows = 50000

```
selection = sel_df_cat.iloc[:, [0,1]]
debt_collection = selection[selection['Product'] == "Debt collection"].head(10)
print(debt_collection)
```

```
             Product                    Consumer complaint narrative
12   Debt collection  This company refuses to provide me verificatio...
16   Debt collection  This complaint is in regards to Square Two Fin...
49   Debt collection  I am writing to request your assistance in loo...
107  Debt collection  My identity was stolen. I filed a complaint, p...
190  Debt collection  The first communication that I received from t...
227  Debt collection  My complaint is n't about phone calls, but I b...
230  Debt collection  In a clearance interview a company was reporte...
235  Debt collection  i gave a vehicle away signed a bill of sale an...
249  Debt collection  Years ago when they first harassed me about th...
255  Debt collection  I have asked real time solutions several times...
```

```
print(clf.predict(count_vect.transform(debt_collection['Consumer complaint narrative'])))
```

```
['Debt collection' 'Debt collection' 'Debt collection' 'Debt collection'
 'Debt collection' 'Debt collection' 'Debt collection' 'Debt collection'
 'Debt collection' 'Debt collection']
```

```
mortgage = selection[selection['Product'] == "Mortgage"].head(10)
print(mortgage)
```

```
      Product                       Consumer complaint narrative
25   Mortgage  Started the refinance of home mortgage process...
26   Mortgage  In XXXX, I and my ex-husband applied for a ref...
29   Mortgage  Mortgage was transferred to Nationstar as of X...
69   Mortgage  Need to move into a XXXX facility. Can no long...
85   Mortgage  I had an FHA loan at US Bank that was paid off...
95   Mortgage  I went through a divorce several years ago and...
118  Mortgage  Select Portfolio Servicing has been deceptive ...
161  Mortgage  I got recent modification ( XXXX/XXXX/2015 ) f...
172  Mortgage  I was late on my mortgage payments and decided...
175  Mortgage  Requested a payoff quote by fax and certified ...
```

```
print(clf.predict(count_vect.transform(mortgage['Consumer complaint narrative'])))
```

```
['Mortgage' 'Mortgage' 'Debt collection' 'Debt collection' 'Mortgage'
 'Mortgage' 'Debt collection' 'Mortgage' 'Mortgage' 'Debt collection']
```

Feature Engineering

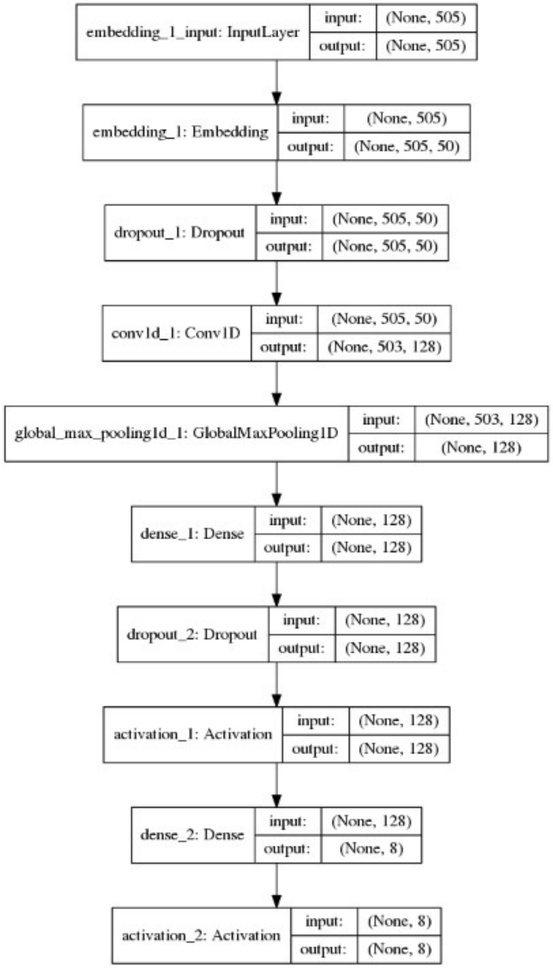
- Word Embeddings: Transforming text into a meaningful vector or array of numbers.

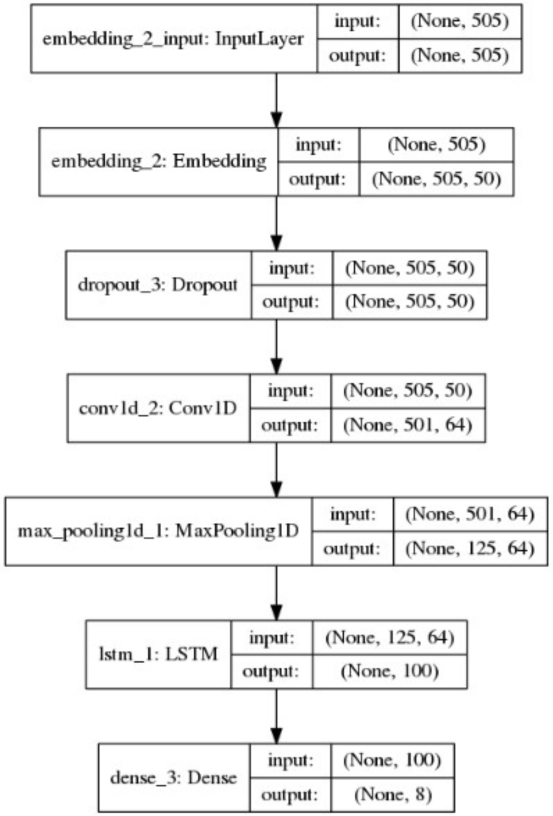
- N-grams : An unigram is a set of individual words within a document; bi-gram is a set of 2 adjacent words within a document.

- TF-IDF values: Term-Frequency-Inverse-Document-Frequency is a numerical statistic representing how important a word is to a document within a collection of documents.

```python
# Feature Engineering to encode the text to sequences and to encode the label to categorical sequences
def sentences_to_sequences(X):
    token = Tokenizer(num_words=vocab_size, filters='!"#$%&()*+,-./:;<=>?@[\]^_`{|}~ ', lower=True, split=' ')
    token.fit_on_texts(X)
    X_seq = token.texts_to_sequences(X)
    X_seq = sequence.pad_sequences(X_seq, maxlen=max_doc_len)
    return X_seq

def label_encoding(y, num_cls):
    le = LabelEncoder()
    y_en = le.fit_transform(y)
    y_en = to_categorical(y_en, num_classes= num_cls)
    return y_en
```

Modelling:
Deep Learning (CNN VS LSTM)

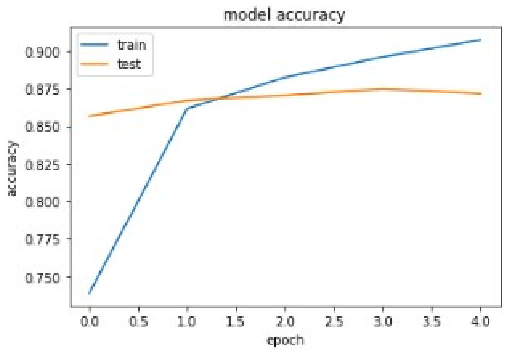


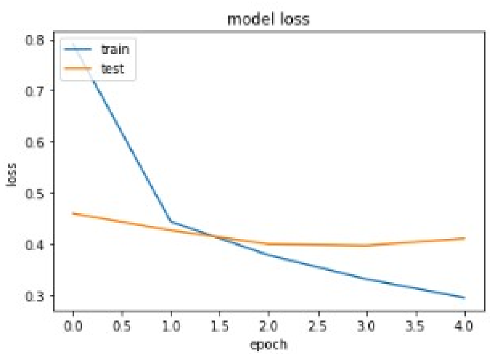


Training & Evaluation:
Deep Learning (CNN VS LSTM)

CNN

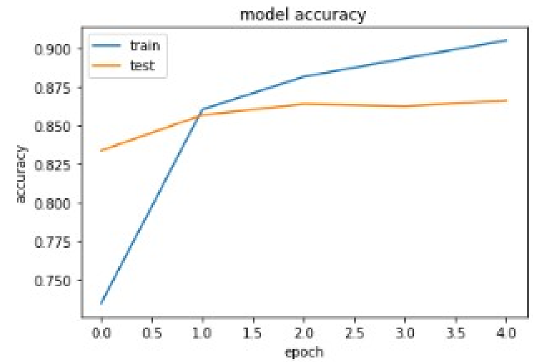
loss: 0.2956 - acc: 0.9074 - val_loss: 0.4111 - val_acc: 0.8716
Epoch 00005: val_acc did not improve from 0.87472
Training time: 89.4 s

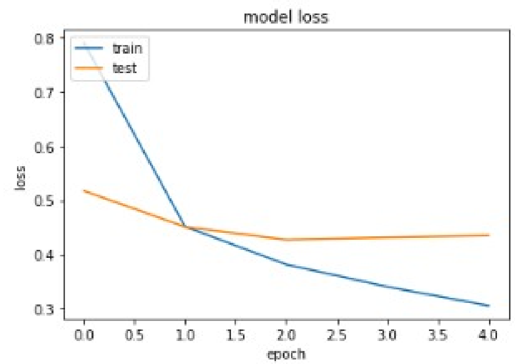




LSTM

loss: 0.3062 - acc: 0.9047 - val_loss: 0.4351 - val_acc: 0.8659
Epoch 00005: val_acc improved from 0.86365 to 0.86593
Training time: 995.3 s





Evaluation:
Deep Learning (CNN VS LSTM)

GINKGO ANALYTICS

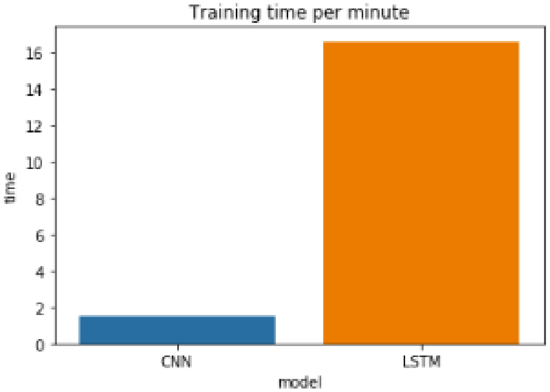
Observations:

- Based on the plots, both CNN and LSTM have similar accuracy and validation accuracy. Even CNN has a slightly higher accuracy.

- CNN model outperformed in terms of training time. I knew that training LSTM could be forever, that's why we still need convolutional layer to make it faster.

- However, LSTM has a positive and consistent trend in the validation accuracy. On the other hand, CNN has a negative trend / more overfitting in the next possible epochs.

- LSTM is popular for many-to-many solutions, but for this classification problem many-to-one solution. CNN, for the win!



Evaluation:
Deep Learning (CNN VS LSTM)

Hyperparameters:

max_features: 40330
max_len: 505
epochs: 5
batch_size: 128
filters: 128
kernel_size: 3
hidden_dims: 128

Optimization Strategies:

Adam Optimization
Manual Hyperparameter Tuning

Regularization:

Dropout
EarlyStopping
ModelCheckpoint

Testing:

```
index = 60
x_test = np.array([sel_df_cat.iloc[index, 1]])
y_result = np.array([sel_df_cat.iloc[index, 0]])
X_test_indices = sentences_to_sequences(x_test)
le = LabelEncoder()
le.fit_transform(sel_df_cat['Product'])
print('Narrative: ' + x_test[0] + ', Expected Product: ' + y_result[0] + ', Prediction Product: '+  le.inverse_transform([np.argma
```

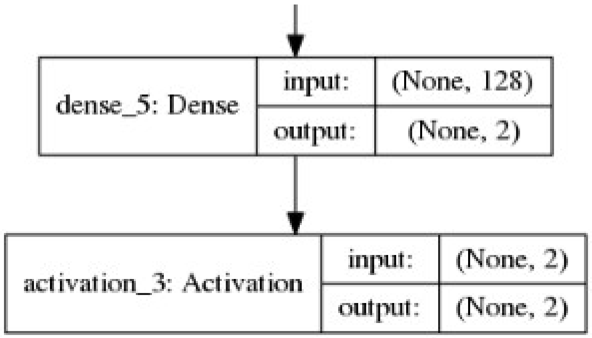
```
['Narrative: Winn Law group continues to pursue me on a debt that was charged off in XX/XX/2011.I have asked them to stop callin
g me & harassing me so now they have threatened to file a judgement against me and continue with collection efforts. I have let
them know that California state law prohibits them from collection activity after 4 years., Expected Product: Debt collection, P
rediction Product: Debt collection']
```

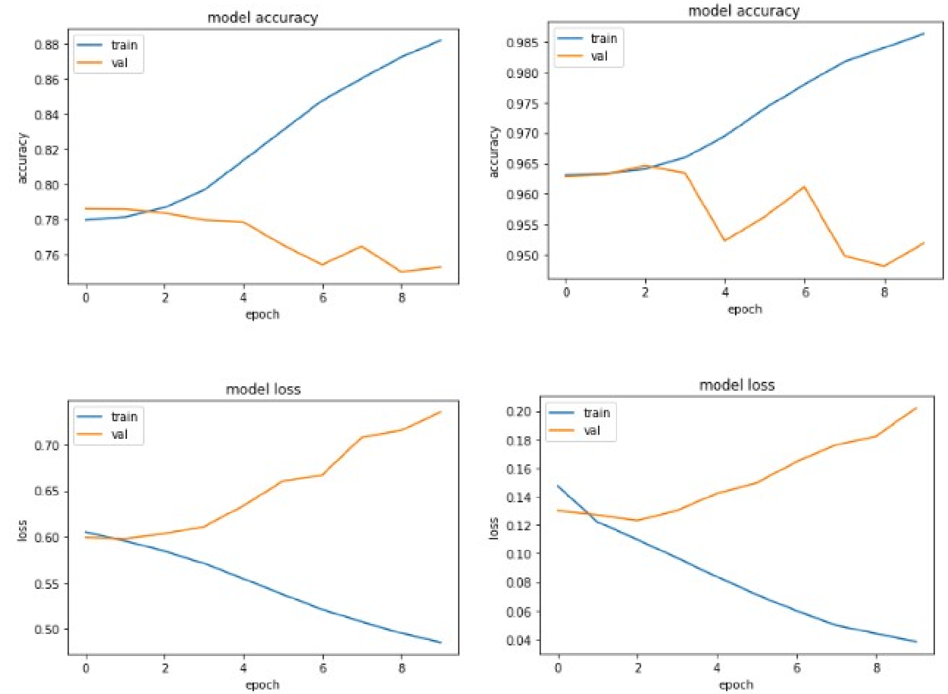
```
x_test = np.array(['I have a problem with my loan and I need the solution fast'])
X_test_indices = sentences_to_sequences(x_test)
le = LabelEncoder()
le.fit_transform(sel_df_cat['Product'])
print('Narrative: ' + x_test[0] + ', Prediction Product: '+  le.inverse_transform([np.argmax(dl_clf.predict(X_test_indices))]))
```

```
['Narrative: I have a problem with my loan and I need the solution fast, Prediction Product: Consumer Loan']
```

Disputed & Timely Response Classifier

Multi-class Classification → Binary Classification
Softmax Layer → Sigmoid Layer
Categorical Crossentropy → Binary Crossentropy





Disputed

Timely Response

Classifiers Testing

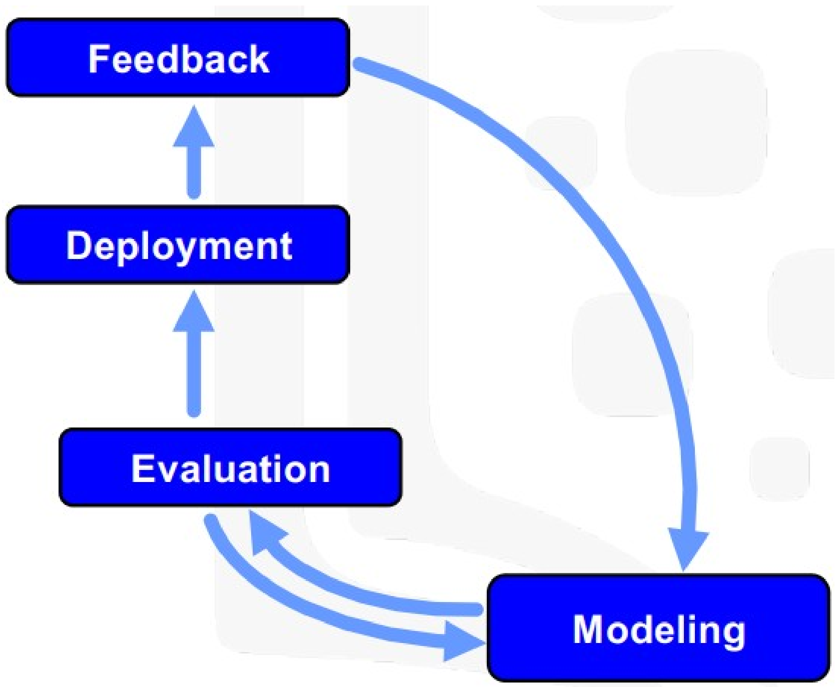
```
index = 60
x_test = np.array([sel_df_cat.iloc[index, 1]])
y_product = np.array([sel_df_cat.iloc[index, 0]])
y_time = np.array([sel_df_cat.iloc[index, 2]])
y_disputed = np.array([sel_df_cat.iloc[index, 3]])
X_test_indices = sentences_to_sequences(x_test)
le_disputed = LabelEncoder()
le_disputed.fit_transform(sel_df_concat['Consumer disputed?'])
le_product = LabelEncoder()
le_product.fit_transform(sel_df_concat['Product'])
le_time = LabelEncoder()
le_time.fit_transform(sel_df_concat['Timely response?'])

print('Narrative: ' + x_test[0])
print('Expected Product: ' + y_product[0] + ', Prediction Product: '+
      le_product.inverse_transform([np.argmax(dl_clf.predict(X_test_indices))]))
print('Expected Timely response: ' + y_time[0] + ', Prediction Timely response: '+
      le_time.inverse_transform([np.argmax(dl_clf_time.predict(X_test_indices))]))
print('Expected Disputed: ' + y_disputed[0] + ', Prediction Disputed: '+
      le_disputed.inverse_transform([np.argmax(dl_clf_disputed.predict(X_test_indices))]))
```

```
Narrative: Winn Law group continues to pursue me on a debt that was charged off in XX/XX/2011.I have asked them to stop calling me
& harassing me so now they have threatened to file a judgement against me and continue with collection efforts. I have let them kno
w that California state law prohibits them from collection activity after 4 years.
['Expected Product: Debt collection, Prediction Product: Debt collection']
['Expected Timely response: Yes, Prediction Timely response: Yes']
['Expected Disputed: No, Prediction Disputed: No']
```

```
x_test = time_yes['Consumer complaint narrative']
X_test_indices = sentences_to_sequences(x_test)
le = LabelEncoder()
le.fit_transform(sel_df_cat['Timely response?'])
predicts = dl_clf_time.predict(X_test_indices)
for predict in predicts:
    print(le.inverse_transform([np.argmax(predict)]))
```

```
['Yes']
['Yes']
['Yes']
['No']
['Yes']
['Yes']
['Yes']
['Yes']
['Yes']
['Yes']
```

Next:
Deployment? Feedback?



https://www-01.ibm.com/events/wwe/grp/grp304.nsf/vLookupPDFs/Polong%20Lin%20Presentation/$file/Polong%20Lin%20Presentation.pdf

Performance Improvements

- More Fine Tuning Hyperparameters: Grid Search, Random Search, ...
- Improve Text Preprocessing with NLP approaches: Lemmatization, NER for finding important entities, Topic Identification in the narratives, …
- Training other features
- Implement other feature engineering approaches (Tfidf, n-grams, factorization).
- Adding more data for minority classes and removing data for majority classes.

Infrastructure Setup:

Kaggle provides 8 core vCPU’s with Nvidia Tesla K80 GPU

Conclusion

- Vanilla ML such as SVM or NB could be an option for training not so large dataset.
- Deep Learning is very robust for the vast amount of data.
- From the consumer complaints narrative, we can build classifier for the Product, Timely response, consumer disputed, ...
- Other predictor variables such as ‘company public response’ could be useful for increasing the performance.
- Would like to try LSTM once having better computational resources.

QuestIOns?

Thank you!
Vielen Dank!
Terimakasih!