SENTIMENT ANALYSIS IN ONLINE REVIEWS

OVERVIEW

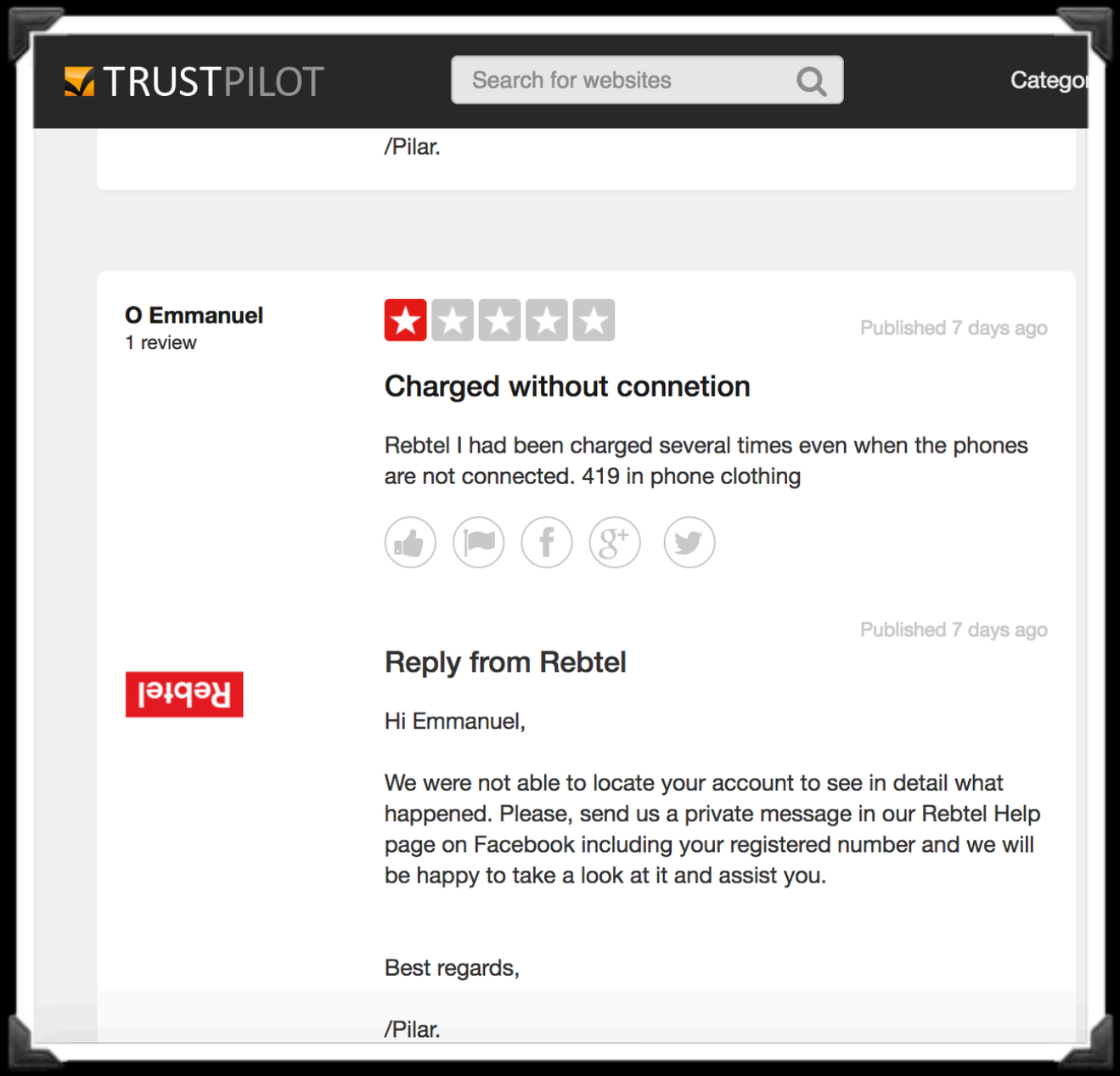
- WHAT IS THE TASK?
- SCRAPE REVIEWS
    - How is the data?
- TEXT PREPROCESSING
    - Cleaning
    - Normalisation
- The VADER Lexicon
- SENTIMENT ANALYSIS MODELS
    - Features (Bag-of-words)
    - Approaches (SVM, NAIVE BAYES, RFC AND MLP)
    - Evaluation (Metrics, Comparison, Insights)
- BUSINESS IMPLICATIONS

The task

- Customer satisfaction in REBTEL
- Predict sentiment of reviews
- Classify rating 1-5 stars

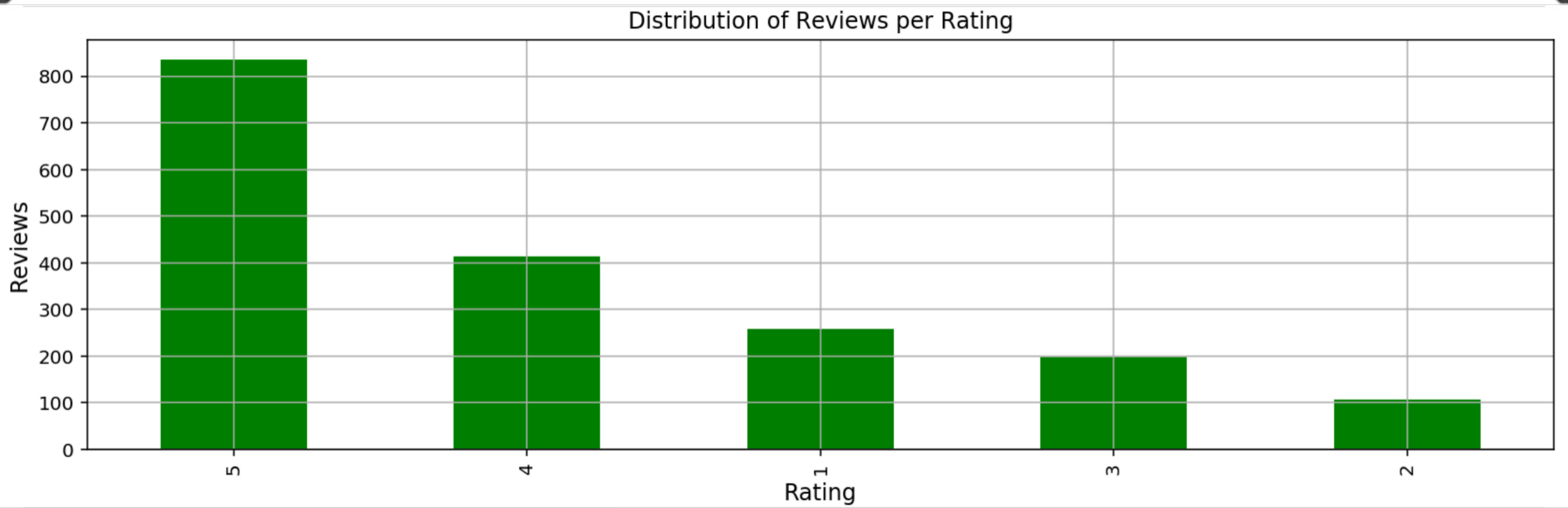
Scrape Reviews

- +2K reviews since 2011
- Information contained:
    - Review
    - Title
    - Rating
    - Time & Date
    - Country
    - Reviews
    - Reads
    - Useful



How is the data?

- REVIEW = TITLE + REVIEW + RATING
- Filter ENGLISH written reviews
- Rating 1-5 stars
- IMBALANCED CLASSES



Text preprocessing

- Tokenisation
- Stop words
- NOT = negative sentiment
- !!! = negative sentiment
- Placeholders: NUM, PRICE
- Check spelling
- Lemmatisation & Stemming

```
print("This is an instance of the raw data: \n","Review : ",raw_data["Review"][0],
      "\n Title : ", raw_data["Title"][0])
```

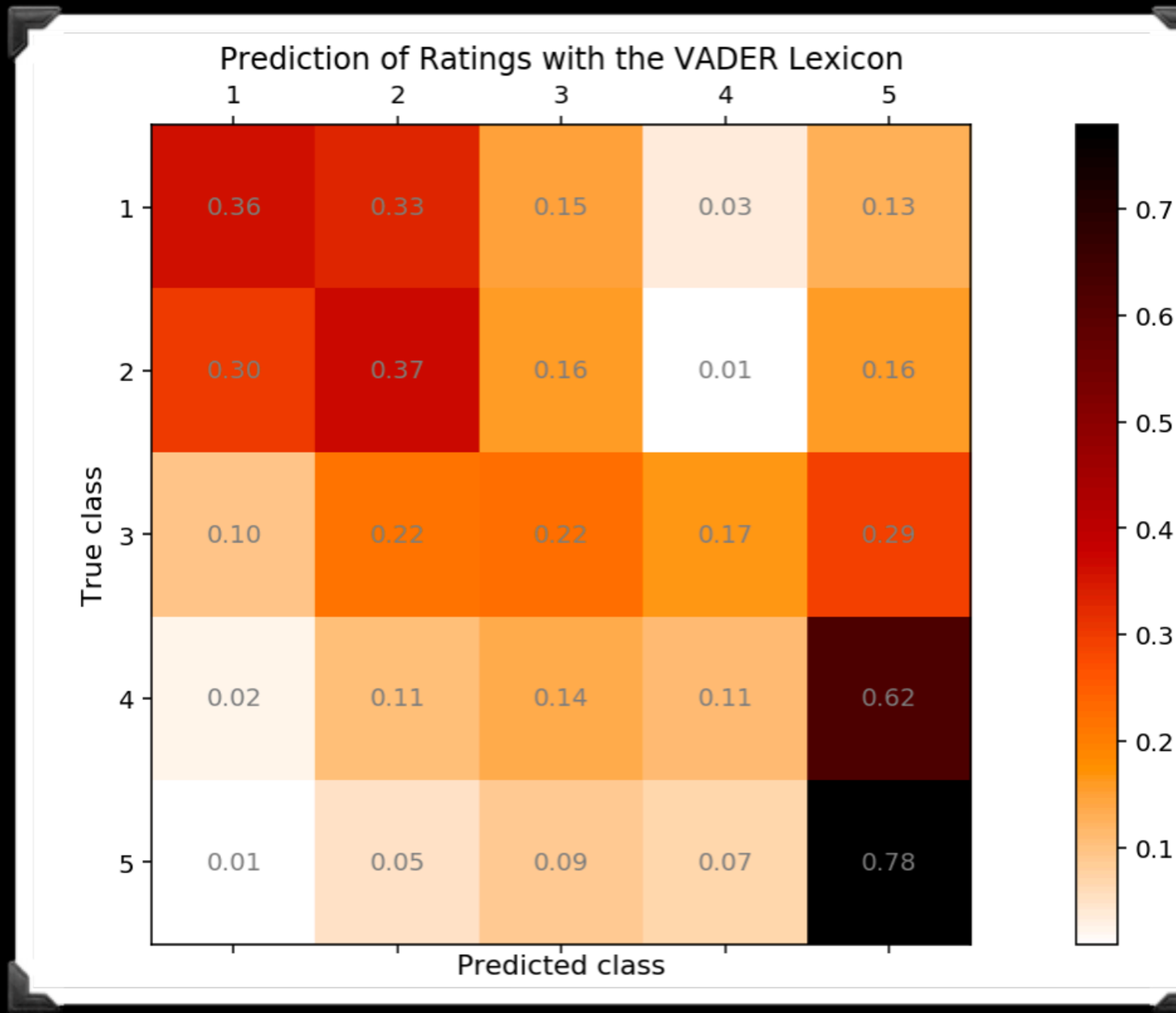
```
This is an instance of the raw data:
 Review :  Rebtel I had been charged several times even when the phones are not connected. 419 in phone clothing
 Title :  Charged without connetion
```

```
print("This is the same instance preprocessed: \n","Review preprocessed: ",p_data["Rel_w_review"][0],
      "\n Title preprocessed : ",p_data["Rel_w_title"][0],
      "\n Title + Review with Stemming : ", p_data["Snow_title_review"][0])
```

```
This is the same instance preprocessed:
 Review preprocessed:  COMPANY charged several times even phones not !connected  NUM phone clothing
 Title preprocessed :  charged without connection
 Title + Review with Stemming :  charg without connect compani charg sever time even phone not ! connect num phone cl
oth
```

The VADER Lexicon

- Rule-based tool
- Sensitive: word-order relationships and punctuation marks
- Detects: SUX! and “Kinda”
- Measures:
    1. Compound
    2. POS, NEG, NEU
- Based on Lexical information
- Reviews with same original structure
- Limitations: Typos, Length Review, Unknown words




```
The misspelled title of the review is:  Theives!!!!
Its score is neutral:  {'neu': 1.0, 'compound': 0.0, 'neg': 0.0, 'pos': 0.0}
```

Sentiment Classifiers models

1. Features

- Bag-of-words representation
- Boolean, Term-frequency and Tf-idf
- N-gram models
- PCA: Most representative attributes

Sentiment Classifiers models

2. Imbalanced classes

- Weighted Samples
- Oversampling (Random oversampling)

3. Model optimisation

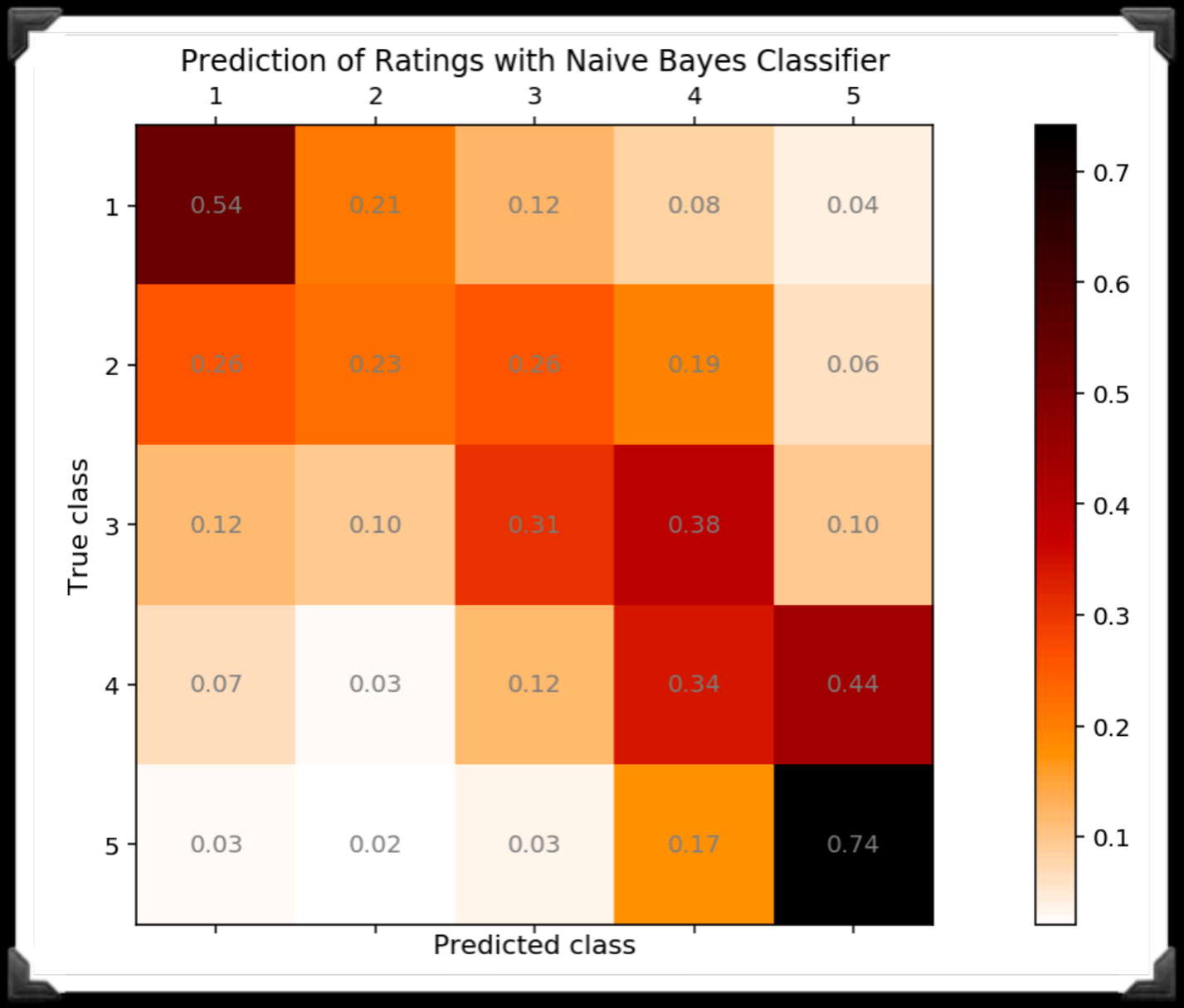
- Greed Search + Cross-validation
- Bagging

4. Metrics

- Precision, Recall and F-score
- NOT Accuracy

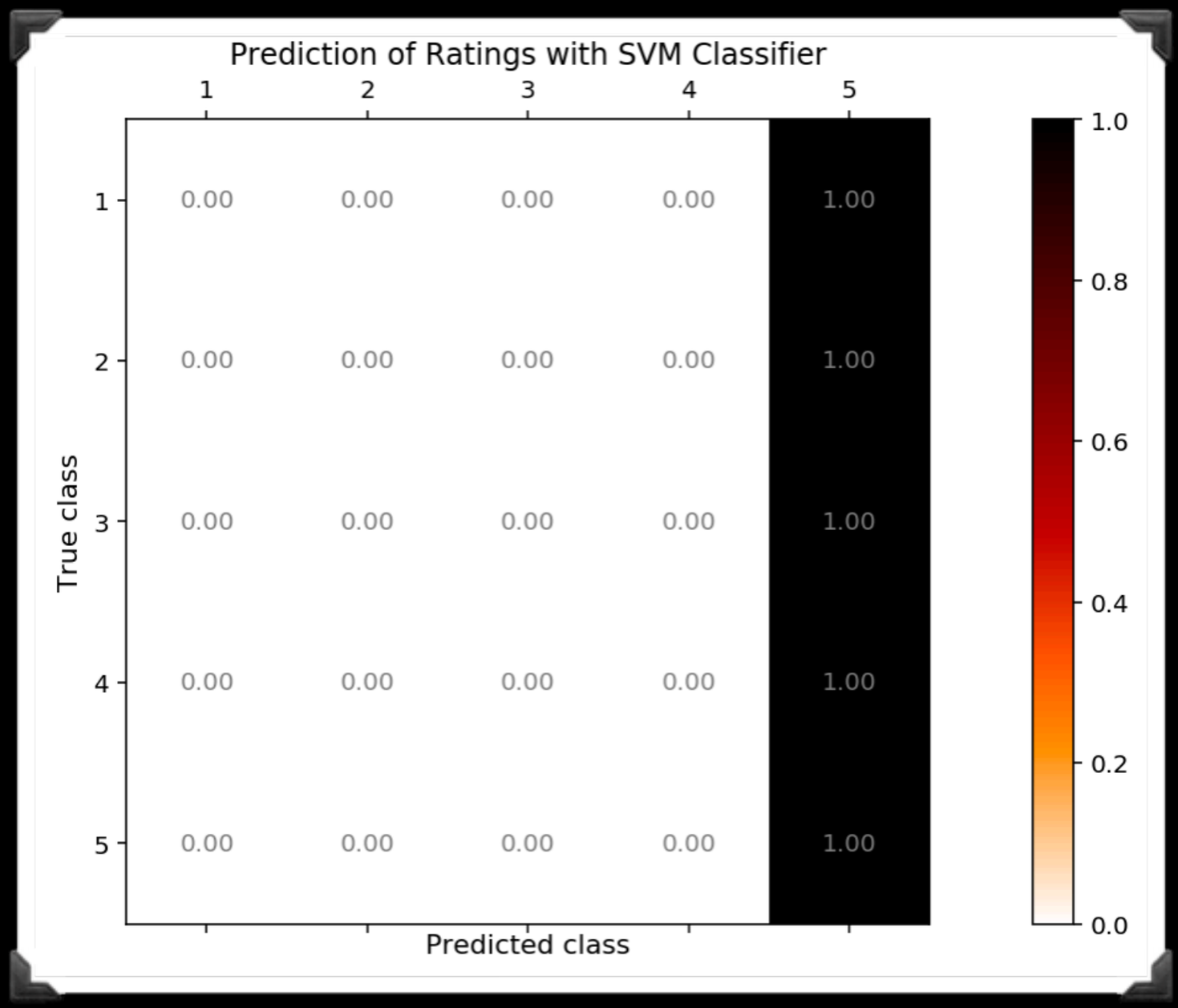
Naive Bayes

- Multinomial NB
- Precision: 60%
- Recall: 58%
- F-Score: 59%
- Accuracy: 58%



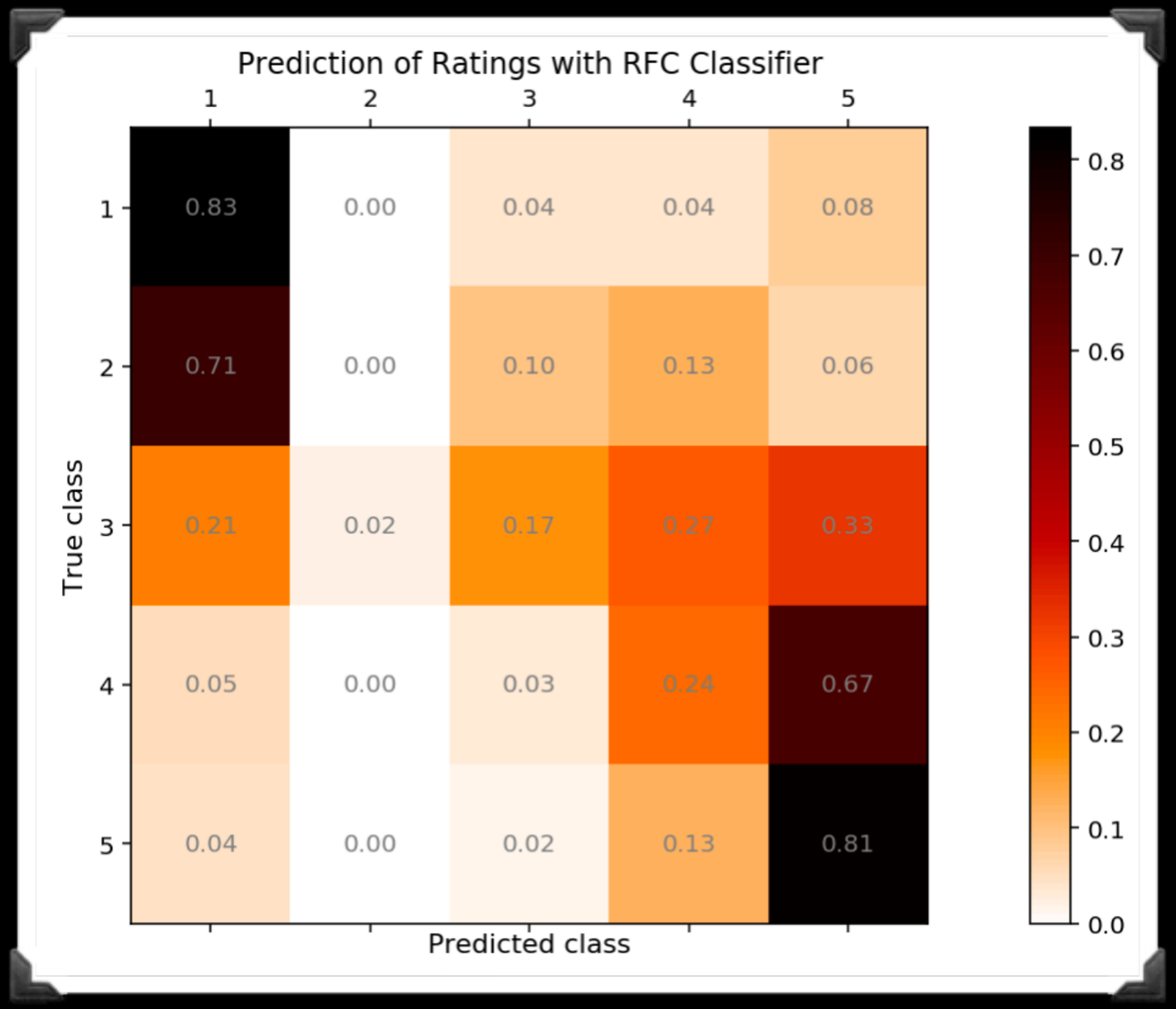
SVM

- RBF Kernel
- Precision: 38%
- Recall: 62%
- F-Score: 47%
- Accuracy: 61%!



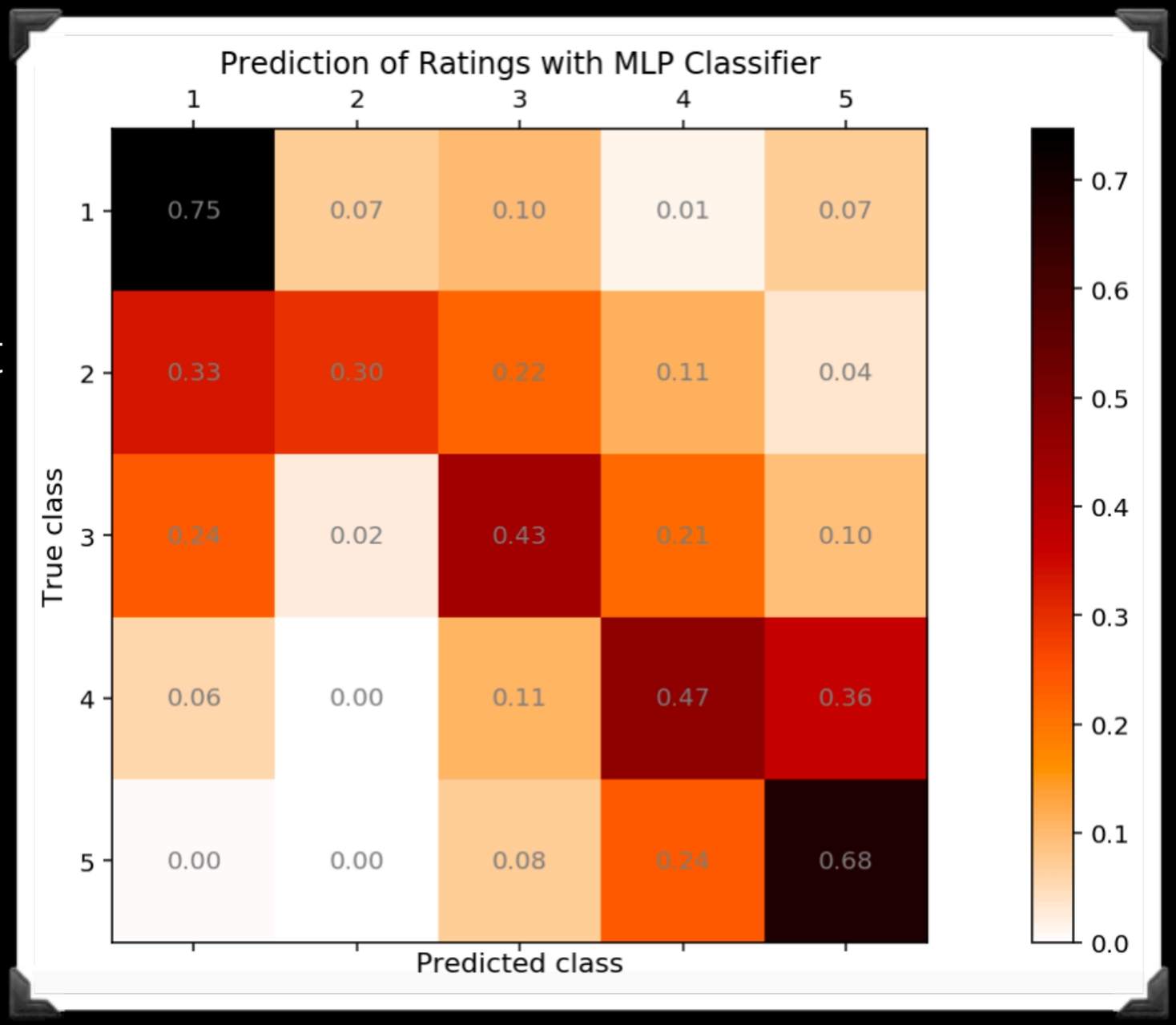
RFC

- 37 Trees, 245 words
- Precision: 55%
- Recall: 59%
- F-Score: 56%
- Accuracy: 58%



Multi-Layer Perceptron

- Fully connected NN. 1 hidden layer with 32 neurons.
- Optimiser: ADAM gradient descent optimisation
- Precision: 62%
- Recall: 60%
- F-Score: 60%
- Accuracy: 59%



Sentiment Classifiers models

5. Evaluation

Model	Precision	Recall	F-Score	Accuracy
NB	60%	58%	59%	58%
SVM	38%	62%	47%	61%
RFC	55%	59%	56%	58%
MLP	62%	60%	60%	59%

6. Next Steps

- Reviews (2,3 and 4 stars) high level ambiguity even for humans!

- Manual data curation = better data quality

Business Implications

- Impact

- Tool direct contact with customers
- Holistic understanding of customers
- Customers post reviews voluntarily. Avoid predisposition to more synthetic surveys.
- Complement metrics for better business decisions

- Application

- Models updated constantly:
    - Detect Market dynamics (regions customers face problems)
- Extended for semantic analysis: (trends social media, compare competitors)
- Challenge: Understand evolution and expectation of customers.

Q&A

Thank you!