# What to ask Questions about?

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## Motivation

### Identifying question-worthy tokens

- Finding bias in the data set
- First step in a question generation pipeline
- Finding important information / concepts

| Answer type | Percentage | Example |
|---|---|---|
| Date | 8.9% | 19 October 1512 |
| Other Numeric | 10.9% | 12 |
| Person | 12.9% | Thomas Coke |
| Location | 4.4% | Germany |
| Other Entity | 15.3% | ABC Sports |
| Common Noun Phrase | 31.8% | property damage |
| Adjective Phrase | 3.9% | second-largest |
| Verb Phrase | 5.5% | returned to Earth |
| Clause | 3.7% | to avoid trivialization |
| Other | 2.7% | quietly |

### Evaluation of QA models

- Identifying weaknesses of current QA models
- Compare the performance of three high ranking models
  - BERT (Google AI Language)
  - BiDAF + Self Attention + ELMo (Allen Institute for AI)
  - nlnet (Microsoft Research Asia)

**Can tokens that are very likely to be the answer to a potential question be predicted (question-worthy tokens)?**
**Does this have an impact on the performance of QA systems?**

## The Stanford Question Answering Dataset (SquAD 2.0)

- 150,000 questions about 19,000 paragraphs
- Created my Crowdworkers on Amazon Mechanical Turk
- **Question-worthy tokens**:
  - Answers sequences of answerable & plausible answer sequences of unanswerable questions
  - Tokens in a paragraph that humans find it interesting to ask questions about

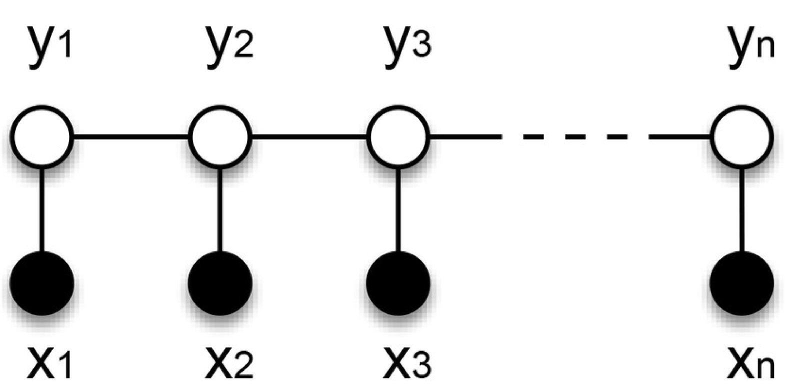
### Overview of the data set

| | Training data | Test data |
|---|---|---|
| Texts / paragraphs | 442 / 19,035 | 35 / 1,204 |
| Question-worthy tokens (I) | 351,862 | 35,214 |
| Non-question-worthy tokens (0) | 2,244,574 | 141,594 |
| Mean paragraph length | 136 | 147 |

## Identifying question-worthy Tokens

### Model

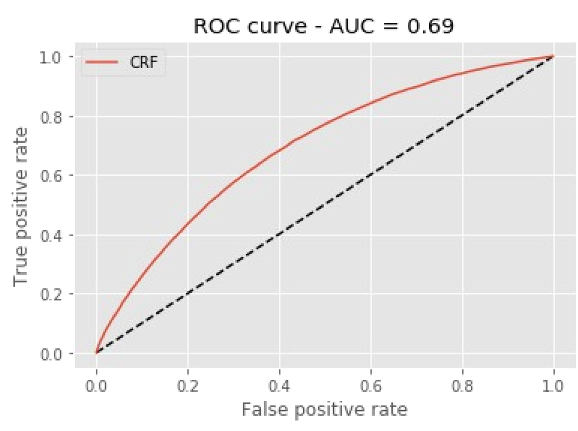
- Conditional Random Field (CRF)
  - implemented using sklearn_crfsuite
  - cross validation of hyperparameters on random subset
- Features
  - Lemma of the words
  - POS Tags
  - Named Entities
  - Dependencies (ClearNLP Dependency Labels)
  - Stopwords
  - Position in the Text




### Evaluation

- Evaluation metrics
  - Precision, Recall, F1-Score
  - ROC-Curve (AUC)
  - Log Loss

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| I | 0.53465 | 0.00153 | 0.00306 | 35214 |
| 0 | 0.80103 | 0.99967 | 0.88939 | 141594 |
| avg / total | 0.74797 | 0.80087 | 0.71286 | 176808 |




Log Loss: 0.48

| y=I top features | |
|---|---|
| **Weight?** | **Feature** |
| +0.351 | 0:word.ent_iob_:B |
| +0.306 | 0:word.pos_:NUM |
| +0.306 | 0:word.tag_:CD |
| +0.285 | 0:word.like_num |
| +0.217 | 0:word.is_digit() |
| +0.205 | 0:word.dep_:pobj |
| +0.195 | 0:word.dep_:nsubj |
| +0.195 | -1:word.tag_:`` |
| +0.167 | -1:word.pos_:VERB |
| +0.167 | 1:word.tag_:'' |
| +0.163 | 0:word.dep_:appos |
| +0.156 | -1:word.is_stop |
| *… 1264 more positive …* | |
| *… 615 more negative …* | |
| -0.155 | 1:word.dep_:compound |
| -0.160 | -1:word.like_num |
| -0.180 | 0:word.dep_:punct |
| -0.186 | 0:word.pos_:PUNCT |
| -0.212 | 0:word.tag_:VBD |
| -0.214 | 1 EOS |
| -0.215 | 0:word.pos_:VERB |
| -0.299 | 0:word.tag_:. |
| -0.302 | -1:word.dep_:pobj |
| -0.340 | 0:word.lemma:. |
| -0.342 | 0:word.dep_:ROOT |
| -0.366 | 0:word.is_stop |
| -0.449 | 1:word.ent_iob_:B |

### Examples

Formed in November 1990 by the equal merger of Sky Television and British Satellite Broadcasting , BSkyB became the UK 's largest digital subscription television company . Following BSkyB 's 2014 acquisition of Sky Italia and a majority 90.04 % interest in Sky Deutschland in November 2014 , its holding company British Sky Broadcasting Group plc changed its name to Sky plc . The United Kingdom operations also changed the company name from British Sky Broadcasting Limited to Sky UK Limited , still trading as Sky .

In England , the period of Norman architecture immediately succeeds that of the Anglo - Saxon and precedes the Early Gothic . In southern Italy , the Normans incorporated elements of Islamic , Lombard , and Byzantine building techniques into their own , initiating a unique style known as Norman - Arab architecture within the Kingdom of Sicily .

## Evaluation of QA models

- Correct prediction: the predicted answer is a substring of the correct answer (or vice versa)

Comparison of the question worthy scores of the correct and predicted answer tokens

### BERT (Google AI Language)

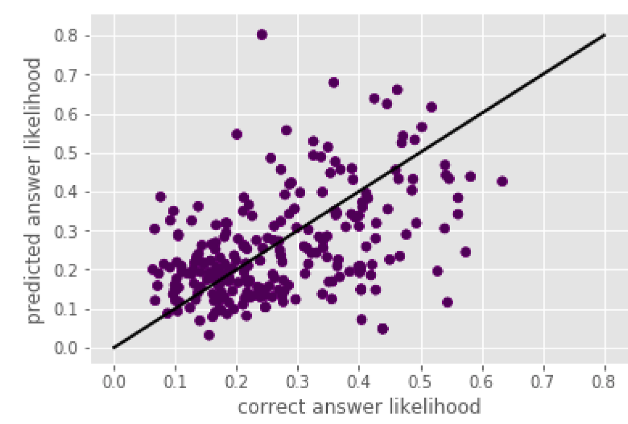
F1: 83.06

| | | True condition: answerable | True condition: unanswerable |
|---|---|---|---|
| Predicted condition | answerable | 4874 | 989 |
| | | 179 | |
| | unanswerable | 826 | 4956 |


### BiDAF + Self Attention + ELMo (Allen Institute for AI)

F1: 66.25

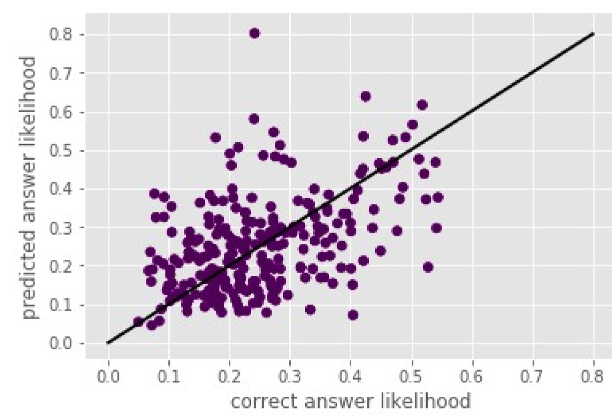
| | | True condition: answerable | True condition: unanswerable |
|---|---|---|---|
| Predicted condition | answerable | 4000 | 1785 |
| | | 243 | |
| | unanswerable | 1657 | 4160 |




### nlnet (Microsoft Research Asia)

F1: 90.13

| | | True condition: answerable | True condition: unanswerable |
|---|---|---|---|
| Predicted condition | answerable | 4586 | 1069 |
| | | 260 | |
| | unanswerable | 1040 | 4876 |




Correct prediction   Wrong prediction

## Results

- Especially Numbers and Named Entities have a very high propability to be asked about
- This can be caused by a bias in the data set:
  - people were getting paid for creating as many questions as possible
  - it is easier to ask about dates and names
- Modern / state-of-the-art Deep Learning approaches make only a few mistakes (mostly related to unanswerable questions)
  - The likelihood of the answer tokens does not play a major role