# Dialogue Breakdown Detection in Chatbots


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# Outline


Introduction

Data & Methods
- Dataset
- Model Type & Architecture
- Word Embedding Models

Implementation
- Data Preprocessing
- Models Development

Evaluation
- Evaluation Metrics
- Evaluation Results

Conclusion

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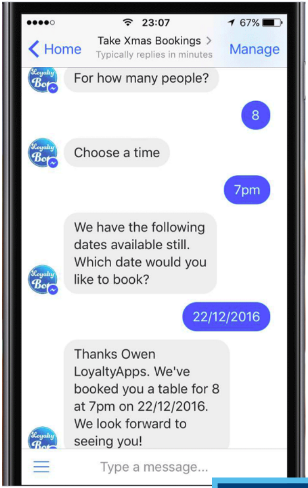
# Chatbot

- A chatbot is a dialogue system which conducts a conversation with a user via text or speech.
- The popularity of chatbots increase.
- Instant 24 hours service
- Usage categories: website help, education, customer service, e-commerce, entertainment, etc.



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# Dialogue Breakdown

- Breakdown is a point in a dialogue when the interaction is interrupted with or without completion of the performed task [Martinovsky and Traum, 2006]

It's nice to *go shopping alone*.
I agree. That's nice.
Shopping takes time.
Window shopping is also fun.
It's fun to *go shopping with somebody*.

Chatbot utterances are red.

# About the Project

- Aim: create a dialogue breakdown detection model
- Research questions:
  - Before building the model
    - What models for breakdown detection are available?
    - Which types of models perform better?
  - After building the model
    - How does the architecture of the model influence its performance?
    - How does the embedding type of the detector influence its performance?

# Contributions

- Overview and comparison of the existing dialogue breakdown detectors
- Introduction of dialogue breakdown detection models which outperform the baseline
- Exploration of relationship between model architecture and its performance
- Investigation of the relationship between embedding type and detector's performance

# Related Literature

- Dialogue breakdown detection challenge:
  - introduced in [Ryuichiro et al., 2015]
  - three challenges held [Higashinaka et al., 2016, 2017]
  - fourth challenge will be held during IWSDS 2019 [dbd]
- Applications:
  - re-ranking system responses [Inaba and Takahashi]
  - aggregating utterances that can be used as system responses [Sugiyama, 2016]

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# Dataset

- Dataset from the Dialogue Breakdown Detection Challenge 3 [dbdc33]
- Dialogues sources:
  - chatbots IRIS, Tick-Tock, 'Yura and Idris'
  - Conversational Intelligence Challenge
- Labels: NB, PB, B
- Classes are balanced
- 30 annotators per system utterance

# Baseline Definition

Based on the overview of existing models performance, we chose two models for the baseline:

- accuracy baseline
- $F_1(B)$ and $F_1(PB+B)$ baseline

| Baseline type | Model | Score |
| --- | --- | --- |
| Accuracy | LSTM + word2vec | 0.44 |
| $F_1(B)$ | MemNN + attention | 0.36 |
| $F_1(PB+B)$ | MemNN + attention | 0.87 |

Table: Baseline Models



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# Model Type & Architecture

- Model Type: Why LSTM?
  - can process sequential data
  - handles long-term dependencies
- Selected architecture types:
  - vanilla LSTM
  - stacked LSTM
  - bidirectional LSTM

# Word Embedding Models Selection

- Limited data $\implies$ pretrained word embedding models
- For the experiments, we select three word embedding types:
  - word2vec pretrained on Google News, 300D
  - GloVe pretrained on Twitter, 200D
  - GloVe pretrained on Common Crawl, 300D

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# Datasets Preprocessing

- Preprocessing steps:
  - General steps:
    - tokenization (with `nltk.tokenize.casual.TweetTokenizer`)
    - apostrophes contractions replacement, e.g., $that's \rightarrow that\ is$
  - Additional steps:
    - for word2vec pretrained on Google News: punctuation signs removal
    - for GloVe pretrained on tweets: lowercasing
- Dialogues length varies $\Longrightarrow$ padding



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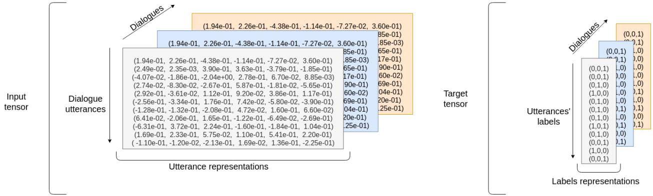
# Representations

- **Token representation** obtained with pretrained embedding model
- **Utterance representation** is the average of the token embeddings comprising the utterances
- **Dialogue representation** is a 2D tensor comprising user and system utterances
- Each **label** is represented with one-hot encoding



# Models Development I

- **Software**: `Python 3.6` with libraries `NumPy`, `NLTK`, `gensim`, `matplotlib`, `sklearn`, `json`. `Tensorflow`(backend) + `Keras`
- **Layers**: one input layer, two hidden layers, one output layer
- **Loss function**: categorical cross-entropy:

$$H(y, \hat{y}) = -\sum_{i=1} y_i log(\hat{y}_i) \tag{1}$$

where $y$ - ground truth label, $\hat{y}$ - predicted label

# Models Development II

- **Mini-batching** with batch size 32
- **Optimization method**: Root Mean Square Propagation (RMSProp)
- **Maximum number of epochs**: 100
- To prevent **overfitting**:
  - Early stopping with patience 5
  - Dropout and recurrent dropout, coefficients set to 0.1



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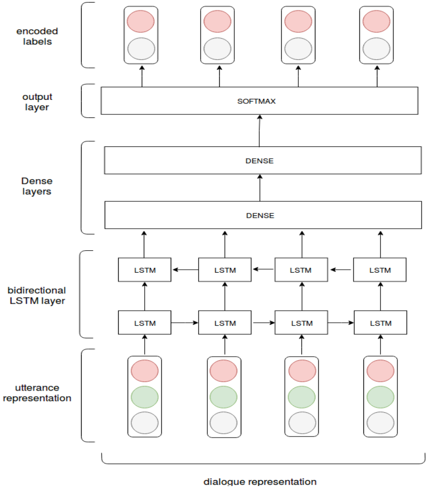
# Bidirectional LSTM

```python
# imports
from keras.models import Sequential
from keras.layers import LSTM, Dense, Bidirectional

# model definition
bi_lstm = Sequential()
# input layer
lstm1 = Bidirectional(LSTM(NUM_CELLS, return_sequences=True, dropout
↪  = DROPOUT_COEFF, recurrent_dropout = DROPOUT_COEFF),
↪  input_shape=(MAX_UTTERANCE_LENGTH, UTTERANCE_DIMENSIONALITY),
↪  merge_mode = 'sum')
bi_lstm.add(lstm1)
# hidden layers
bi_lstm.add(add(Dense(NUM_CELLS, activation = 'relu')))
bi_lstm.add(Dense(NUM_CELLS, activation = 'relu'))
# output layer
bi_lstm = Dense(NB_LABELS, activation = 'softmax')
bi_lstm.add(outputs)

# model compilation
bi_lstm.compile(
    optimizer = 'rmsprop',
    loss = 'categorical_crossentropy',
    metrics=['accuracy'])

# model training
bi_lstm_history = bi_lstm.fit(
    X_train, y_train,
    batch_size=BATCH_SIZE,
    validation_data = (X_test, y_test),
    callbacks = [EarlyStopping(monitor='val_loss',
    ↪  patience=PATIENCE)],
    epochs=NUM_EPOCHS)
```



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# Evaluation Metrics

- **Accuracy**: what fraction of items is classified correctly?
- $F_1$ **score**:
  - Incorporates precision and recall:
    - Precision: how many selected items are relevant?
    - Recall: how many relevant items are selected?
  - A variant of F-score with precision and recall equally important

# Models Performance

| Model | Embedding | Accuracy | $F_1(B)$ | $F_1(PB+B)$ |
|---|---|---|---|---|
| Vanilla LSTM | Google News | 0.42 | 0.38 | 0.84 |
| | GloVe Twitter | 0.41 | 0.31 | 0.78 |
| | GloVe Common Crawl | 0.44 | **0.46** | **0.93** |
| Stacked LSTM | Google News | 0.39 | 0.30 | 0.77 |
| | GloVe Twitter | 0.42 | 0.41 | 0.82 |
| | GloVe Common Crawl | 0.42 | 0.45 | **0.93** |
| Bi-LSTM | Google News | 0.42 | 0.33 | 0.75 |
| | GloVe Twitter | 0.44 | 0.34 | 0.83 |
| | GloVe Common Crawl | **0.46** | 0.37 | 0.85 |

Table: Models performance results. The best performance is indicated in bold

# Comparison with the Baseline

| Model type | Description | Accuracy | $F_1(B)$ | $F_1(PB+B)$ |
|---|---|---|---|---|
| Accuracy baseline | LSTM + word2vec Google News | 0.44 | 0.29 | 0.74 |
| Best accuracy score model | Bi-LSTM + GloVe Common Crawl | **0.46** | 0.37 | 0.85 |
| $F_1$ baseline | MemNN + attention | 0.29 | 0.36 | 0.87 |
| Best $F_1$ score model | Vanilla LSTM + GloVe Common Crawl | 0.44 | **0.46** | **0.93** |

Table: Comparison of the created models with the baseline models. The best performance is indicated in bold

# Relationship Exploration

- LSTM architecture in terms of model performance:
  1. Vanilla LSTM
  2. Stacked LSTM
  3. Bidirectional LSTM
- Word embedding model in terms of detector performance:
  1. GloVe Common Crawl
  2. GloVe Twitter
  3. word2vec Google News

# Patterns in Error Types

As the number of unknown tokens increase, the model performance decrease.

- Emoticons: simple (🙂 🙁) vs. complex (😎 😑)
- Apostrophe contractions:
  - standard, e.g., *isn′t* $\rightarrow$ *is not*
  - ambiguous, e.g., *he's* $\rightarrow$ *he has* or *he is*
- Misspellings:
  - standard, e.g., 'seee', 'tommorow'
  - merging words, e.g., 'questionWho', 'wait.Where'
- Abbreviations, e.g., *ConvAI* (Conversational Artificial Intelligence)
- Extra:
  - meaningless sequences of characters (e.g., *MAMAXMAMAX*)
  - tokens representing words from a different language

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# Summary

First part:

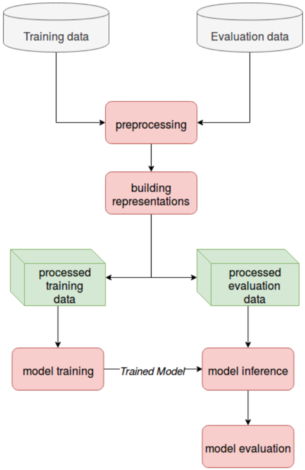
- dataset exploration
- existing models overview
- selection of:
  - baseline
  - model for experiments

Second part:

- dataset preprocessing
- model development

Third part:

- models evaluation
- comparison with the baseline
- exploration of error patterns



# Future Work

- Model architecture: investigate further architecture types, e.g., LSTM with attention
- Word embedding model: experiment with Embeddings from Language Model (ELMo)
- Dataset expansion: including different languages and modalities
- Working with the unknown tokens
- Submitting the model for dialogue breakdown detection challenge 4

Thank you for your attention!

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Ryuichiro Higashinaka, Kotaro Funakoshi, Michimasa Inaba, Yuki Arase, and Yuiko Tsunomori. The dialogue breakdown detection challenge 2. *Proceedings of SIG-SLUD*, 2016.

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# Bibliography III

Higashinaka Ryuichiro, Kotaro Funakoshi, Yuka Kobayashi, and Inaba Michimasa. The dialogue breakdown detection challenge: Task description, datasets, and evaluation metrics. 2015.

Hiroaki Sugiyama. Utterance selection based on sentence similarities and dialogue breakdown detection on ntcir-12 stc task. In *NTCIR*, 2016.



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# Appendix

# Task Setting

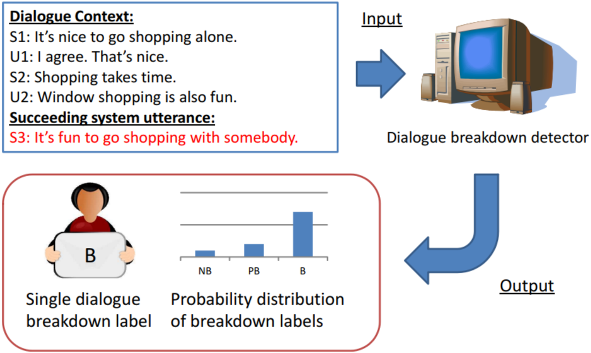


Figure: Task setting [Higashinaka et al., 2017]

# Dialogue Representation in JSON

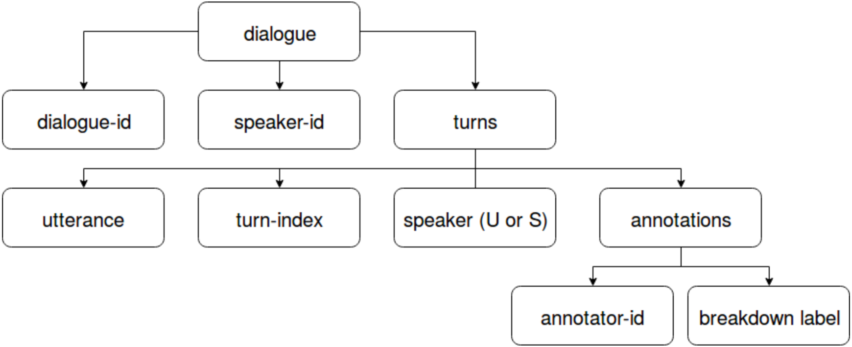


Figure: Dialogue representation in JSON: fields hierarchy


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# The Dataset Statistics

| | Development data | | | | Evaluation data | | | |
|---|---|---|---|---|---|---|---|---|
| | TKTK | IRIS | CIC | YI | TKTK | IRIS | CIC | YI |
| Dialogues | 100 | 100 | 115 | 100 | 50 | 50 | 50 | 50 |
| Annotators | CF | CF | AMT | AMT | CF | CF | AMT | AMT |
| NB | 35.1% | 32.9% | 28.9% | 34.8% | 44.3% | 34.5% | 29.1% | 35.4% |
| PB | 27.6% | 27.8% | 29.8% | 36.1% | 29.2% | 29.3% | 39.3% | 40.3% |
| B | 37.3% | 39.4% | 41.3% | 29.1% | 26.5% | 36.2% | 31.6% | 24.3% |
| Fleiss' $\kappa$ | 0.14 | 0.11 | 0.05 | 0.01 | 0.13 | 0.09 | 0.001 | -0.006 |

Table: The dataset statistics

# Types of Models

- Conditional Random Fields (CRF)
- Extremely Randomized Trees (ETR)
- Maximum Entropy model (MaxEnt)
- Support Vector Machines (SVM)
- Memory Networks (MemNN)
- Recurrent Neural Networks (RNN). Includes Long Short-term Memory Network (LSTM)
- Models with attention

| Model type | Implementation description | Accuracy | $F_1(B)$ | $F_1(PB+B)$ |
|---|---|---|---|---|
| CRF | baseline model for DBDC3 | 0.420 | 0.354 | 0.762 |
| MaxEnt | *MaxEnt, labelling exchanges | 0.410 | 0.240 | 0.220 |
| SVM | SVM + SpeDial feature set | 0.340 | 0.350 | 0.840 |
| MemNN | MemNN + attention | 0.295 | **0.364** | **0.874** |
| | MemNN + attention; trained on multiligual data | 0.290 | 0.356 | 0.870 |
| ETR | ETR + geometric mean | 0.426 | 0.312 | 0.832 |
| | ETR + cosine similarity of all word pairs | 0.431 | 0.320 | 0.840 |
| | ETR + arithmetic mean | 0.420 | 0.302 | 0.835 |

| Model type | Implementation description | Accuracy | $F_1(B)$ | $F_1(PB+B)$ |
|---|---|---|---|---|
| RNN | RNN + attention between sentences, GloVe Twitter | 0.360 | 0.208 | 0.346 |
| | RNN + attention + GloVe Twitter + finetuning | 0.210 | 0.210 | 0.340 |
| | RNN + attention + GloVe Twitter + extra linguistic features | 0.356 | 0.320 | 0.805 |
| | LSTM + BoW, word embeddings | **0.440** | 0.290 | 0.744 |
| | LSTM + BoW, document embeddings | 0.422 | 0.340 | 0.759 |
| | Hie-Bi-LSTM + GloVe Wikipedia | 0.429 | 0.321 | 0.763 |

Table: Models overview: classification results. The best performance is indicated in bold. An asterisk signifies submission without technical paper

# Datasets Preprocessing

Decisions to make before preprocessing:

- Keep user utterances? Yes, it improves model performance [Lopes]
- ow to feed user utterances? As separate utterances marked with $U$ label

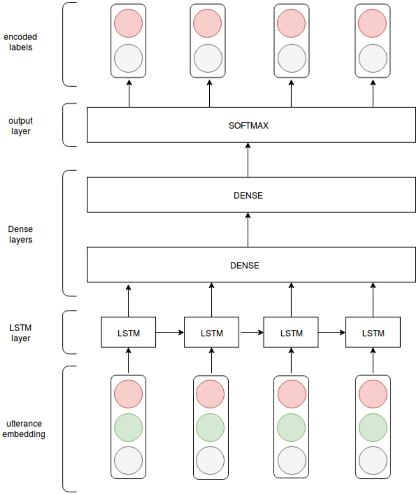
# Vanilla LSTM

```
# imports
from keras.models import Sequential
from keras.layers import LSTM, Dense

# model definition
vanilla = Sequential()
# input layer
lstm1 = LSTM(NUM_CELLS, input_shape=(MAX_UTTERANCE_LENGTH,
↪  UTTERANCE_DIMENSIONALITY), return_sequences=True, dropout =
↪  DROPOUT_COEFF, recurrent_dropout = DROPOUT_COEFF)
vanilla.add(lstm1)
# hidden layers
vanilla.add(Dense(NUM_CELLS, activation = 'relu'))
vanilla.add(Dense(NUM_CELLS, activation = 'relu'))
# output layer
outputs = Dense(NB_LABELS, activation = 'softmax')
vanilla.add(outputs)

# model compilation
vanilla.compile(
    optimizer = 'rmsprop',
    loss = 'categorical_crossentropy',
    metrics=['accuracy'])

# model training
vanilla_history = vanilla.fit(
    X_train, y_train,
    batch_size=BATCH_SIZE,
    validation_data = (X_test, y_test),
    callbacks = [EarlyStopping(monitor='val_loss', patience=5)],
    epochs=NUM_EPOCHS)
```



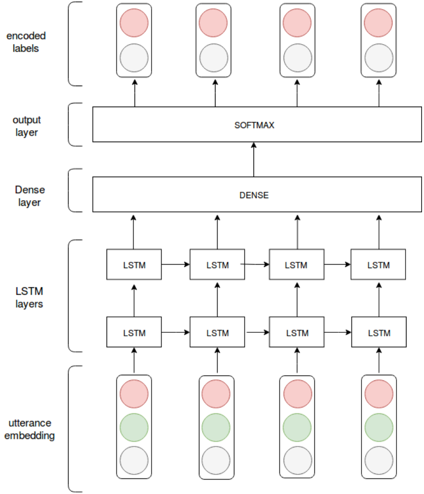
# Stacked LSTM

```
# imports
from keras.models import Sequential
from keras.layers import LSTM, Dense

# model definition
stacked = Sequential()
# input layer
lstm1 = LSTM(NUM_CELLS, input_shape=(MAX_UTTERANCE_LENGTH,
↪  UTTERANCE_DIMENSIONALITY), return_sequences=True, dropout =
↪  DROPOUT_COEFF, recurrent_dropout = DROPOUT_COEFF)
stacked.add(lstm1)
# hidden layers
lstm2 = LSTM(NUM_CELLS, input_shape=(MAX_UTTERANCE_LENGTH,
↪  UTTERANCE_DIMENSIONALITY), return_sequences=True, dropout =
↪  DROPOUT_COEFF, recurrent_dropout = DROPOUT_COEFF)
stacked.add(lstm2)
vanilla.add(Dense(NUM_CELLS, activation = 'relu'))
# output layer
stacked = Dense(NB_LABELS, activation = 'softmax')
stacked.add(outputs)

# model compilation
stacked.compile(
    optimizer = 'rmsprop',
    loss = 'categorical_crossentropy',
    metrics=['accuracy'])

# model training
stacked_history = stacked.fit(
    X_train, y_train,
    batch_size=BATCH_SIZE,
    validation_data = (X_test, y_test),
    callbacks = [EarlyStopping(monitor='val_loss',
    ↪  patience=PATIENCE)],
    epochs=NUM_EPOCHS)
```



# Relationship Exploration

| LSTM type | Accuracy | $F_1(B)$ | $F_1(PB+B)$ |
|---|---|---|---|
| Vanilla LSTM | 0.42 | 0.38 | 0.85 |
| Stacked LSTM | 0.41 | 0.39 | 0.84 |
| Bi-LSTM | 0.44 | 0.35 | 0.81 |

Table: Average metric scores for every LSTM type

| Embedding type | Accuracy | $F_1(B)$ | $F_1(PB+B)$ |
|---|---|---|---|
| word2vec Google News | 0.41 | 0.34 | 0.78 |
| GloVe Twitter | 0.42 | 0.35 | 0.81 |
| GloVe Common Crawl | 0.44 | 0.43 | 0.90 |

Table: Average metric scores for every embedding type

# Answers to Research Questions

- There are several major types of dialogue breakdown detectors: CRF, ETR, MaxEnt, SVM, MemNN, RNN, and models with attention
- Comparison of the existing models allow concluding that LSTM and MemNN appear to produce better results
- Both model architecture and word embedding model influence the performance. Word embedding model appear to produce a more significant impact.