# Email Author Identification

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# Objective

- Identify authors of emails from the ENRON dataset.
- ENRON dataset:
    - **~500,000** emails
    - **153** unique authors - employees of ENRON
    - Released into the public domain after an investigation led to the closure of the company

# Approach

- Familiarizing with existing state-of-the-art document classification techniques
- Studying existing approaches to ENRON specific document classification
- Formalizing the final approach and  further experiments to try and improve upon the existing models

# Phase 1: **Data Preparation**

- Fixed the number of author to allow more experimentation with features
- Number chosen such that
  - the number of emails per author is maximized
  - emails/author ratio is similar across all authors
- This value was found to be **10** authors with **800-1000** emails each

## Phase 1: **Data Preparation**

- Cleaning the corpus
  - The ENRON data consists of raw, unparsed, unclean e-mails
  - Extracting only the **Body** for every email
  - Removing chains of forwarded messages
  - **Word**, **sentence** and **paragraph**-level tokenization
  - Case normalization

# Phase 2: **Existing Neural Models**

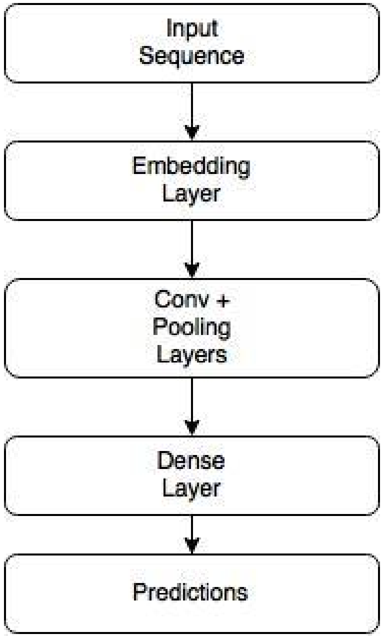
- Explore the state-of the art techniques in document classification and implement them on our dataset
- The models implemented include
  - **CNN**-based model
  - **Bi-LSTM** based model
  - **Hierarchical Bi-LSTM** based model

## Phase 2.1: **CNN-based Model**

- Implementation of ideas from *"Convolutional Neural Networks for Sentence Classification" - Yoon Kim*
- CNNs are known to capture localized chunks of information - this can be useful to find phrasal units within long texts
- Can identify key, commonly used groups of words by an author

# Phase 2.1: **CNN-based Model**

- The **Embedding layer** generates a sequence of word-embeddings from a sequence of words.
- Each **Conv layer** has 128 5x5 filters
- The **Dense layer** is used for classification

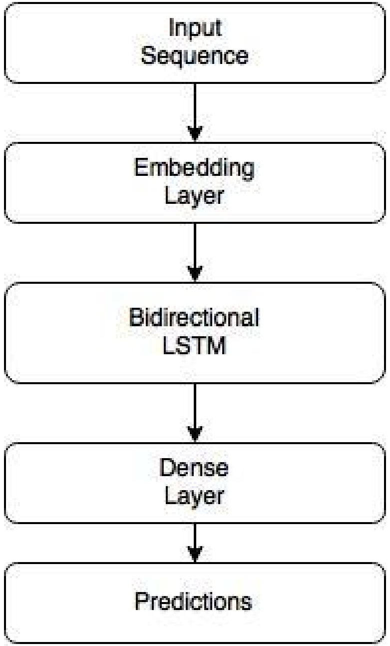


# Phase 2.2: **Bi-LSTM-based Model**

- Standard, commonly used technique in text classification
- LSTMs are a special kind of **RNN** which are more capable of remembering long term dependencies in a sequence
- Helps in author classification as it keeps track of past events while processing a sequence of text

## Phase 2.2: **Bi-LSTM-based Model**

- The **Embedding layer** generates a sequence of word-embeddings from a sequence of words
- The **Bidirectional LSTM** generates e-mail embeddings from the sequence of word embeddings
- The **Dense layer** is for the classification

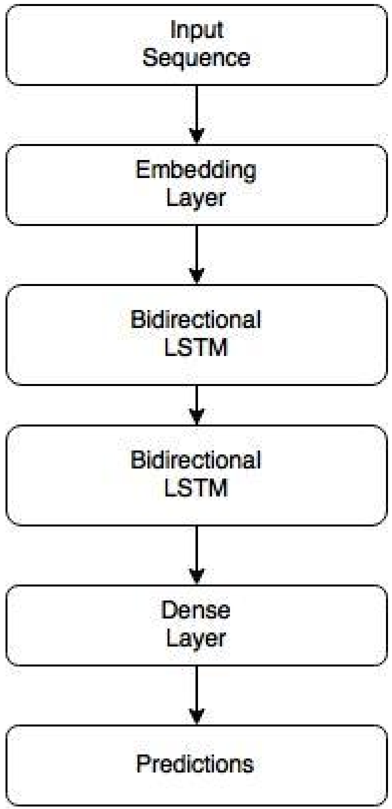


## Phase 2.3: **Hierarchical Bi-LSTM Model**

- Idea based on *"Hierarchical Attention Networks for Document Classification" - Yang et. al.*
- LSTMs are known to work best for a sequence length of 10-15 elements
- In a Hierarchical LSTM,
  - The first level generates sentence-embeddings from word-embeddings
  - The second level generates email-embeddings from sentence-embeddings

# Phase 2.3: **Hierarchical Bi-LSTM Model**

- The Embedding layer generates a sequence of word-embeddings from a sequence of words
- The first Bidirectional LSTM generates sentence embeddings from the sequence of word embeddings
- The second Bidirectional LSTM generates e-mail embeddings from sentence embeddings
- The Dense layer is for the classification



## Phase 2.4: **Results**

- The best validation accuracies obtained for each of the models are given below

| | |
|---|---|
| **CNN model** | **56.43%** |
| **Bi-LSTM** | **73.54%** |
| **Hierarchical Bi-LSTM** | **77.04 %** |

- As anticipated, the Hierarchical Bi-LSTM model performs the best

# Phase 3: Stylometric Features

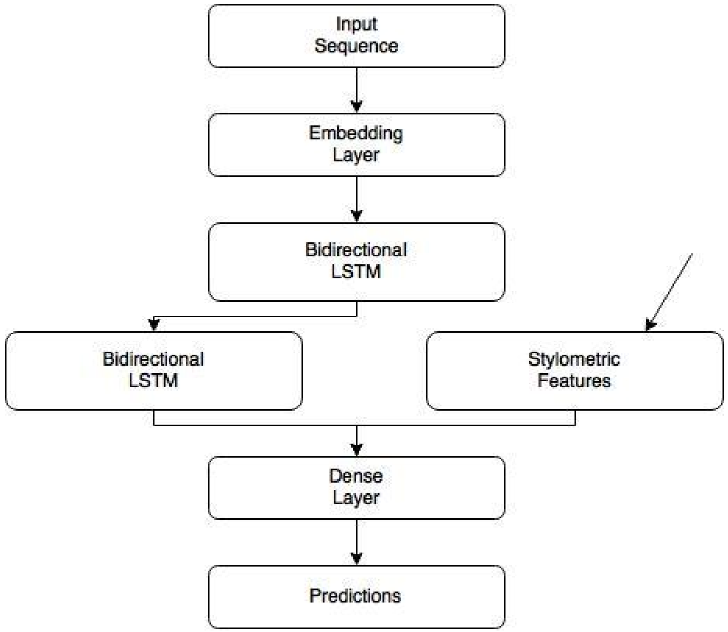
- Models tried so far are generally useful for document classification tasks
- Emails stand apart from documents in  two major ways
  - Short text length
  - Lack of topical difference
- So, existing work specific to the ENRON dataset rely on stylometric features.
- Stylometric features capture certains writing styles specific to authors
- We attempt to augment our Hierarchical Bi-LSTM model with these stylometric features in an attempt to improve performance.

# Phase 3.1: **Stylometric Feature Extraction**

- The following stylometric features were extracted per author per e-mail:
- **Lexical:**
    - Average sentence-length
    - Average word-length
    - Total number of words
    - Ratio of unique words to total number of words
    - Total number of characters
- **Syntactic:**
    - Total number of function words
    - Total number of personal pronouns
    - Total number of adjectives

# Phase 3.2: **Augmenting Hierarchical Bi-LSTM Model**

- The stylometric features are appended in the Hierarchical Bi-LSTM model, before the final email embedding is passed on to the Dense layer for classification
- The classification is then done on these augmented email-embeddings



# Phase 3.3: **Final Results**

- The most discriminating features were found to be
  - Ratio of unique words to total words
  - Number of adjectives
  - Average word-length
  - Average sentence-length
- The best validation accuracy obtained was ~78% (~1% increase over the basic Hierarchical Bi-LSTM model)

# References:


- *CEAI: CCM-based email authorship identification model* - Serwat Nizamani, Nasrullah

- *Writeprints: A stylometric approach to identity-level identification and similarity detection in cyberspace* - Ahmed Abbasi, Hsinchun Chen

- *Detection of Fraudulent Emails by Authorship Extraction* - A. Pandian, Mohamed Abdul Karim

# Thank you!