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## ❖ Introduction

### ➤ Task:

Identifying dataset surface forms (dataset mention extraction; **subtask A**) and associating the extracted mention to its referred dataset (dataset classification; **subtask B**).

#### Publication:

....Source: [Monitoring the Future: National Survey on Drug Use, 1975-2009](#) .... Section 2 provides a brief summary of trends in adolescent drinking and smoking, using data for the US from the annual [Monitoring the Future survey](#) .... Trends in Adolescent Drinking and Smoking: [Monitoring the Future](#) .... Systematic annual data on the prevalence of underage drinking and smoking in the US are collected and tracked by several organizations. This section relies on data from the [Monitoring the Future \(MTF\)](#) ....

#### Datasets (Present): [ ...

56: [Monitoring the Future: A Continuing Study of the Lifestyles and Values of Youth, 1984](#);

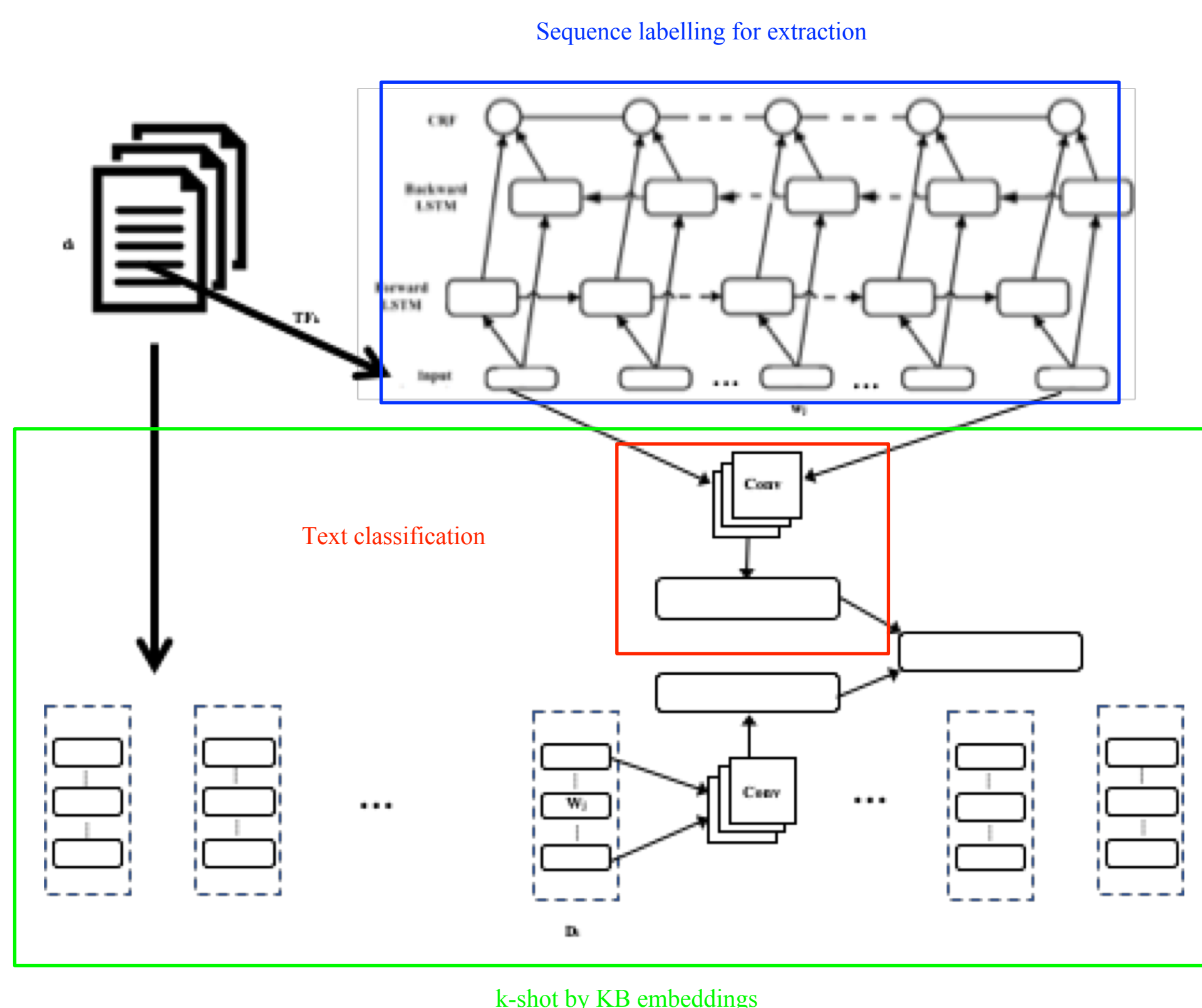
101: [Monitoring the Future: A Continuing Study of the Lifestyles and Values of Youth, 1989](#); ...]

#### Datasets (Not Present): [ ...

100: [Monitoring the Future: A Continuing Study of American Youth \(12th-Grade Survey\)](#), 1996;

108: [Current Population Survey, May 1973](#); ...]

## ❖ Models



### ➤ Shared Layer Extraction-Classification ('SL E-C')

Share the output from the CNN-BiLSTM-Attn base, and substitute the CRF layer with a CNN layer for dataset classification.

### ➤ KB Shared Layer Extraction-Classification ('KBSL E-C')

In this model, we leverage on the meta-information (description) of the dataset knowledge base to better support zero-shot learning

## ❖ Experiments & Results

### ➤ Scenarios:

One-plus classification, zero-shot classification and zero-shot discovery

### ➤ Modeling Decisions:

Size of the text-fragment

Sampling negative text-fragment

### ➤ Evaluation:

On the **dev set**, the **test set** and on the **zero-shot test set**.

- 1) Randomly held out 7% of the datasets from the corpus and select the publications (219 documents in total) containing these datasets to form **zero-shot test set**.
- 2) Randomly hold out 225 publications to form the **test set**.
- 3) The **dev set** is split from the training set (5%) and has the same distribution and length as the training set.

| Model               | Partial |      |             | Exact |      |             |
|---------------------|---------|------|-------------|-------|------|-------------|
|                     | P       | R    | F1          | P     | R    | F1          |
| BiLSTM              | 29.4    | 32.1 | 30.7        | 11.2  | 12.8 | 12.0        |
| CNN-BiLSTM          | 49.8    | 44.7 | 47.1        | 28.6  | 31.2 | 29.8        |
| CNN-BiLSTM-CRF      | 54.1    | 44.8 | 48.9        | 35.6  | 33.8 | 34.7        |
| CNN-BiLSTM-Attn-CRF | 58.0    | 50.0 | <b>53.7</b> | 34.8  | 38.0 | <b>36.4</b> |
| SL E-C              | 40.3    | 43.1 | 41.7        | 27.1  | 28.4 | 27.7        |

Performance of **test set** for mention extraction

| Model  | P    | R    | F1          |
|--------|------|------|-------------|
| BiLSTM | 27.5 | 47.4 | 34.8        |
| CNN    | 42.8 | 46.5 | <b>44.6</b> |
| SL E-C | 31.8 | 49.3 | 38.6        |

Performance of **test set** for classification

## ❖ Observations & Conclusion

We find CNN-BiLSTM-CRF and CNN models work best for dataset mention extraction and classification respectively.

Though appears to be a pipeline tasks strict pipeline configurations give poorer performance.

We identify that while mention extraction is primarily dependent on local signals the dataset classification uses a much wider context than just the mention.

*Though the task appears to be easy for human turns out to be challenging for models due to extreme high output space and sparse per output signals.*