

# **Knowledge-Base-Enriched Relation Extraction**

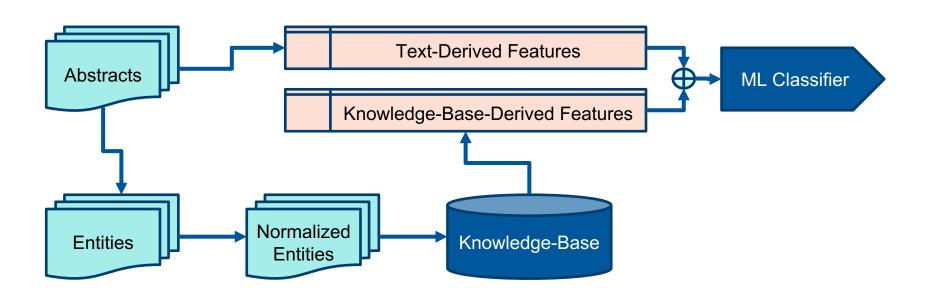
#### **BioCreative VI, Task 5**

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## **Mixed Approach**



## Identified potential relations

- Assumed any chemicals and proteins/genes in the same sentence as potentially related
- Chemical/protein combinations not addressed by given relations labeled as "NONE"
- Relations outside of task scope pooled as "OTHER"

## Identified potential relations

... cetuximab (IMC-225, Erbitux). Agents that have only begun to undergo clinical evaluation include CI-1033, an irreversible pan-erbB tyrosine kinase inhibitor, and PKI166 and GW572016, both examples of dual kinase inhibitors (inhibiting epidermal growth factor receptor and Her2). Preclinical models have demonstrated...

| PKI166   | erbB                             | NONE  |
|----------|----------------------------------|-------|
| PKI166   | tyrosine kinase                  | NONE  |
| PKI166   | kinase                           | CPR:4 |
| PKI166   | epidermal growth factor receptor | CPR:4 |
| PKI166   | Her2                             | CPR:4 |
| GW572016 | erbB                             | NONE  |
| GW572016 | tyrosine kinase                  | NONE  |
| GW572016 | kinase                           | CPR:4 |
| GW572016 | epidermal growth factor receptor | CPR:4 |
| GW572016 | Her2                             | CPR:4 |

#### **Extracted features from text**

- Entity 1
- Entity 2
- Entity 1 + Entity 2
- Text in between entities
- Text along dependency path between entities (unigrams up to trigrams)
- Labels of the dependency path between entities (unigrams up to trigrams)
- Words from entire sentence

## **Knowledge-base Of Biomedicine (KaBOB\*)**

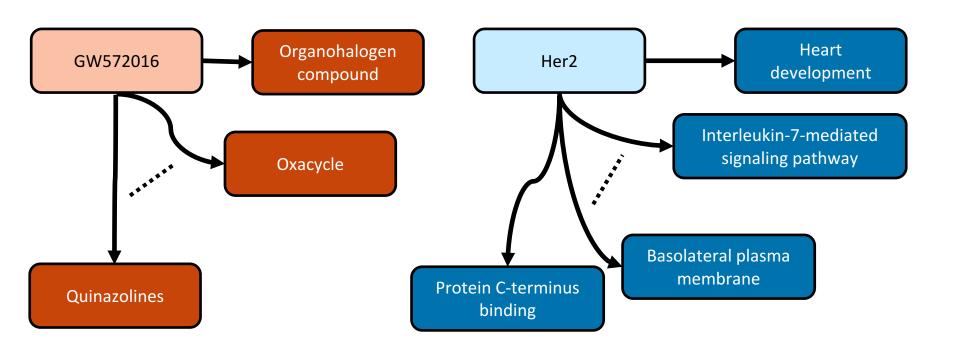
- AllegroGraph RDF triple store (~280 million triples) based on the Open Biomedical Ontologies
- Integrates 17 public biomedical ontologies
- Data from 13 public databases
- Semantically consistent
- SPARQL Endpoint

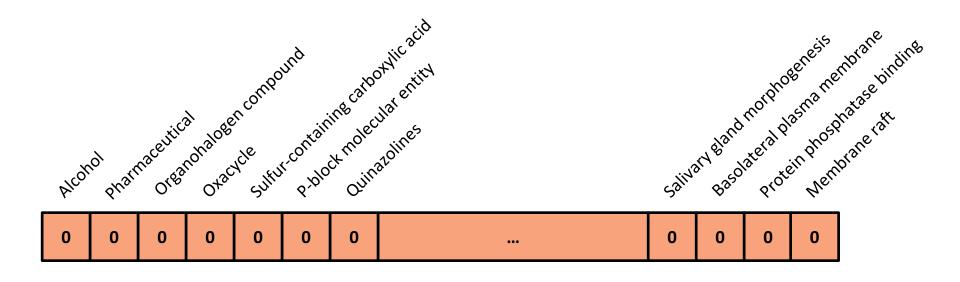
#### Mapped chemicals to ChEBI IDs

Queried relevant parent classes

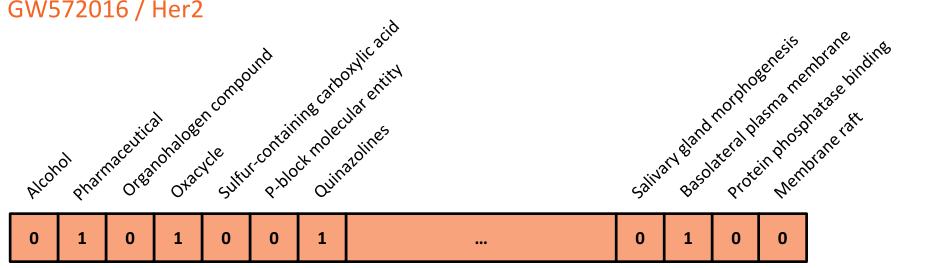
### Mapped proteins/genes to PRO IDs

Queried related biological processes, molecular functions and cellular components

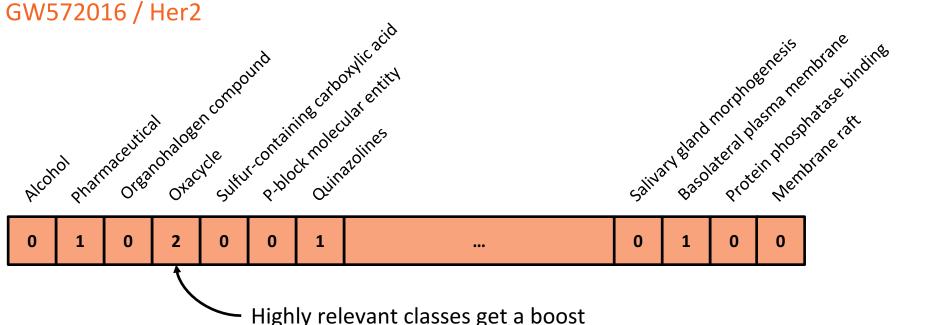




GW572016 / Her2



GW572016 / Her2



## Tested multiple classifier configurations

- KaBOB features
- Tokens from the entire sentence
- Feature selection of 10k, 20k and 30k top features
- Include trigrams from words in dependency path
- Multiple machine learning classifiers: Random Forests, Perceptron, Naïve Bayes,
  Neural Networks

## **Results**

| Relation       | Training Data Performance Metrics |        |         |  |
|----------------|-----------------------------------|--------|---------|--|
|                | Precision                         | Recall | F-Score |  |
| CPR:3          | 0.76                              | 0.74   | 0.75    |  |
| CPR:4          | 0.79                              | 0.80   | 0.80    |  |
| CPR:5          | 0.60                              | 0.60   | 0.60    |  |
| CPR:6          | 0.61                              | 0.74   | 0.67    |  |
| CPR:9          | 0.75                              | 0.83   | 0.79    |  |
| NONE           | 0.92                              | 0.91   | 0.91    |  |
| OTHER          | 0.72                              | 0.75   | 0.73    |  |
| AVG /<br>TOTAL | 0.86                              | 0.86   | 0.86    |  |

| Run   | <b>Evaluation Performance Metrics</b> |        |         |  |
|-------|---------------------------------------|--------|---------|--|
|       | Precision                             | Recall | F-Score |  |
| Run 1 | 0.3460                                | 0.3913 | 0.3673  |  |
| Run 2 | 0.3387                                | 0.4078 | 0.3700  |  |
| Run 3 | 0.3305                                | 0.1666 | 0.2215  |  |
| Run 4 | 0.3307                                | 0.3641 | 0.3466  |  |
| Run 5 | 0.3058                                | 0.3603 | 0.3309  |  |

#### Results

- KaBOB features alone not yet enough to classify relations
- Tokens from the entire sentence introduced too much noise
- Using all features was worth the performance improvement over feature selection
- Best training performance accomplished by Neural Networks, Perceptron and Naïve Bayes, in that order

## **Future steps**

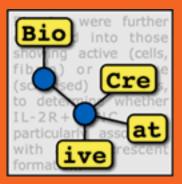
- Improve KaBOB queries to extract more features
- Explore most relevant KaBOB features to use as prior probabilities in other applications
- Find top shortest paths between a chemical and drug node in KaBOB
- Better tuning of classifiers
- Discriminate across all relation types (no "OTHER" class)

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## **Questions?**