

NLP course 2023

# Homework 3

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## Relation Extraction

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# Relation Extraction

An introduction



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# What is a Relation?

- A **relation** can be defined as a binary or n-ary association between two or more entities.
- Relations are represented as tuples consisting of a relation type and the entities that participate in the relationship.
- For example, the relation "works at" might involve a person (subject of the relation) and a company (object of the relation).



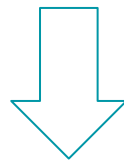
# Relation Extraction

- **Relation Extraction** is a Natural Language Processing task that involves identifying and extracting relationships between entities mentioned in text.
- **Goal:** extract structured information from unstructured data by identifying the type of relationship between entities, such as "born in", "works at", "married to", etc.
- We limit our case study only to **binary relations**.

# Relation Extraction

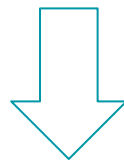
## Example

“This Must Be the Place” is a song by new wave band Talking Heads, released in November 1983 as the second single from its fifth album “Speaking in Tongues”.



Identify entities that contain relations

“**This Must Be the Place**” is a song by **new wave** band **Talking Heads**, released in November 1983 as the second single from its fifth album “**Speaking in Tongues**”.



Extract triplets made of (subject entity, relation type, object entity)

(**This Must Be the Place**, performer, **Talking Heads**)  
(**Talking Heads**, genre, **new wave**)  
(**This Must Be the Place**, part of, **Speaking in Tongues**)  
(**Speaking in Tongues**, performer, **Talking Heads**)

# Dataset

# The Dataset

- Each sample is a sentence annotated with **relation tuples** (subjects, relation types and objects) that appear in the sentence.
- There may be **multiple relation tuples** in a given sentence.
- Data splits:
  - **56196** training examples (`train.jsonl`)
  - **5000** development examples (`dev.jsonl`)
  - **2000** test examples (`test.jsonl`)

# Dataset format

- JSONL, i.e. each line is a JSON object with two fields:
  - **tokens**: the pre-tokenized sentence, i.e. a list of tokens that make up the sentence.
  - **relations**: a list of relation tuples. Each element of the list is a relation tuple made of a dictionary with 3 keys:
    - subject: containing start and end token indexes, entity type and lexical representation.
    - relation: e.g. "/location/country/capital"
    - object: containing start and end token indexes, entity type and lexical representation.



# Dataset entry

```
{  
  "tokens": ["The", "2023", "chess", "tournament", "was", "held", "in", "Reykjavik", ",", "Iceland", "."],  
  "relations":  
  [  
    {  
      "subject": {  
        "start_idx": 9,  
        "end_idx": 10,  
        "entity_type": "LOCATION",  
        "text": "Iceland"  
      },  
      "relation": "/location/country/capital",  
      "object": {  
        "start_idx": 7,  
        "end_idx": 8,  
        "entity_type": "LOCATION",  
        "text": "Reykjavik"  
      }  
    }  
  ]  
}
```

# Modelling approaches



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# Two-phase pipeline

Simple approach, requires some data-handling skills.

## Phase 1 - Entity recognition:

Predict entities - we don't need their category and they might not be named.

- **Training:** similar to NER notebook, dataset annotations could be converted to IOB labels, ...
- **Inference:** collect all predicted entities and build input for next phase, i.e. all possible combinations of entities.

## Phase 2 - Relation classification:

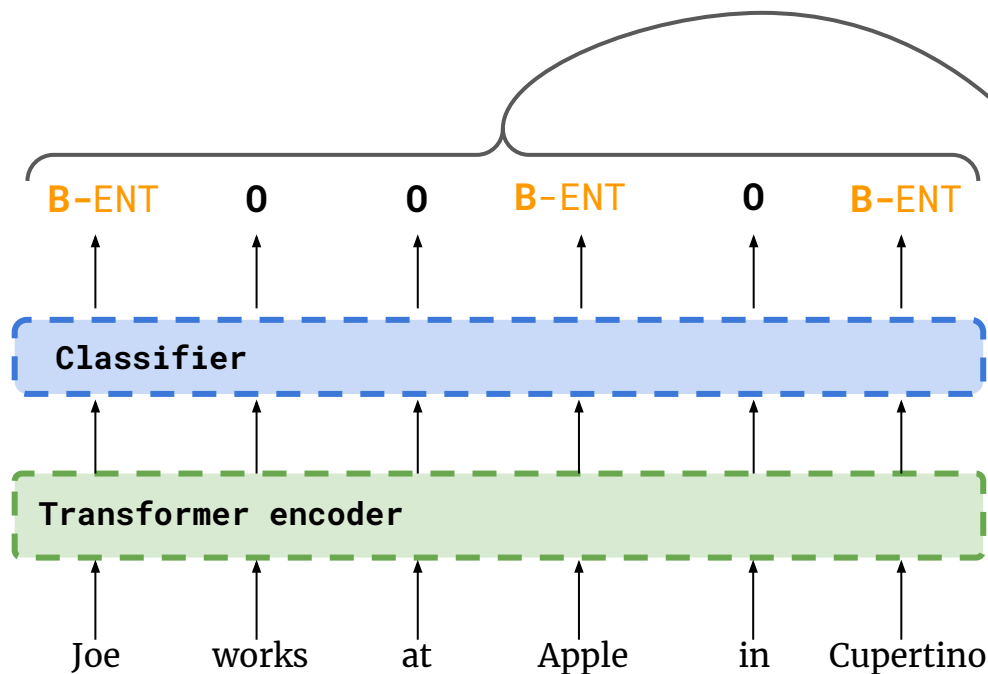
Given a sentence, a subject entity and an object entity, classify their relation.

You **should indicate** to the model **which tokens are the subject and the object**.

- **Training:** convert dataset to have one relation tuple per sample, find a way to identify subject and object
- **Inference:** simply predict the relation for a given sentence, subject and object.

# Two-phase pipeline

## Phase 1 - Entity recognition



Relation tuple candidates:

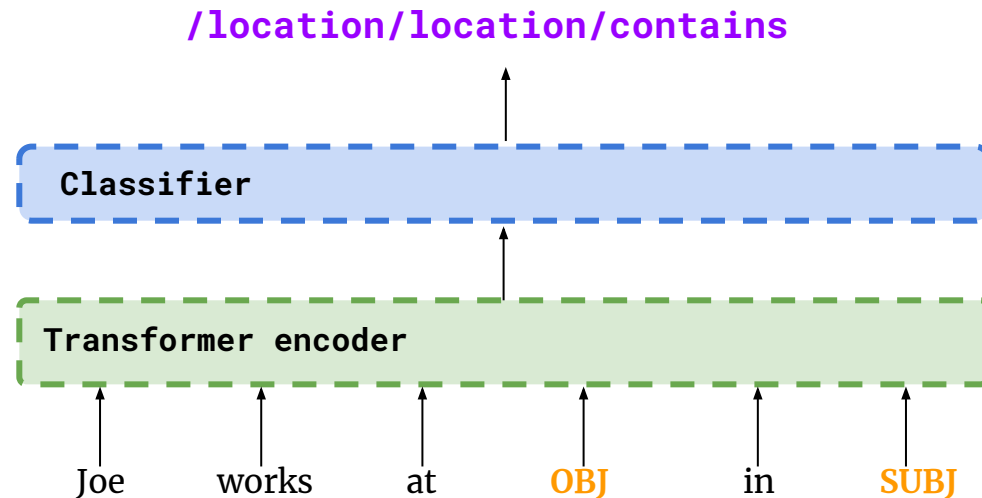
- Joe | Apple
- Joe | Cupertino
- Apple | Joe
- Apple | Cupertino
- Cupertino | Joe
- Cupertino | Apple

# Two-phase pipeline

## Phase 2 - Relation classification

Relation tuple candidates:

- Joe | Apple
- Joe | Cupertino
- Apple | Joe
- Apple | Cupertino
- Cupertino | Joe
- Cupertino | Apple



# Table-filling end-to-end

More complicated approach, must manually implement some steps in the model.

**Main idea:** build a matrix  $A$  having as rows and columns the sentence tokens.

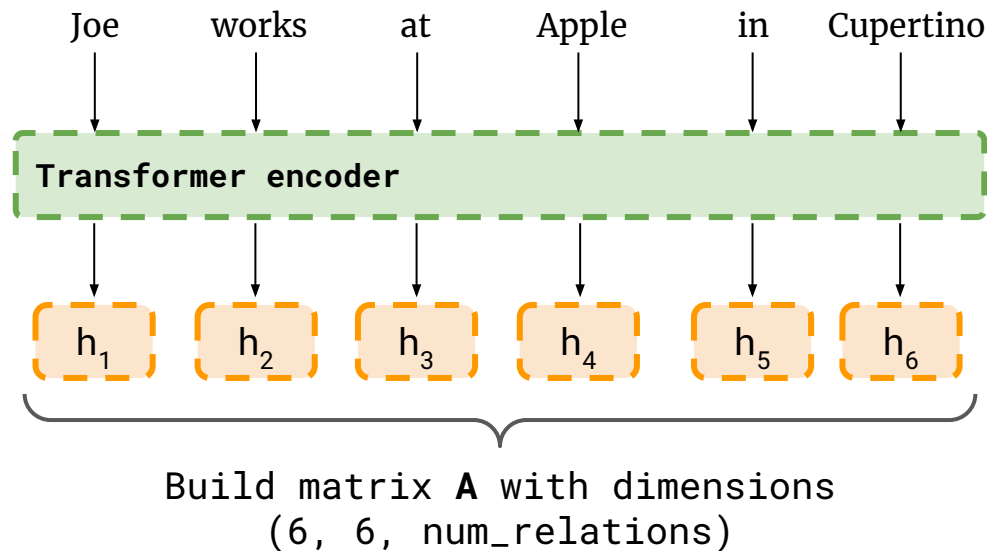
For two given tokens  $i$  and  $j$ ,  $i \neq j$ ,  $A[i, j]$  defines the relation with token  $i$  as subject and token  $j$  as object (can also be *no\_relation*)

## Steps to take:

1. Convert samples from the dataset into this matrix representation;
2. Find a way to derive the matrix through the model:
  - a. element-wise product and projection layer;
  - b. dot product and convolutional layer;
  - c. using attention matrices computed by the transformer;
  - d. ...
3. Measure the loss comparing the modelled matrix with the one you converted from the dataset

# Table-filling end-to-end

## Schematic example



# Table-filling end-to-end

## Matrix example

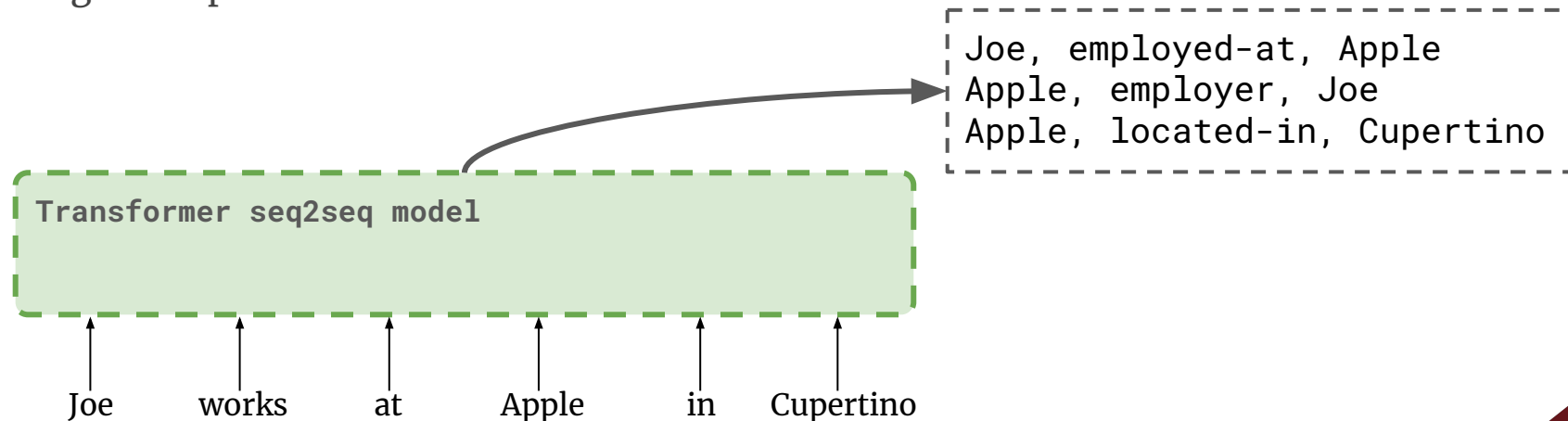
| Subject | Object      |                 |                    |             |                   |
|---------|-------------|-----------------|--------------------|-------------|-------------------|
|         | $h_1$ : Joe | ...             | $h_4$ : Apple      | $h_5$ : in  | $h_6$ : Cupertino |
|         | $h_1$       | ...             | <b>employed-at</b> | no_relation | no_relation       |
|         | ...         | ...             | ...                | ...         | ...               |
|         | $h_4$       | <b>employer</b> | ...                | no_relation | <b>located-in</b> |
|         | $h_5$       | no_relation     | no_relation        | no_relation | no_relation       |
|         | $h_6$       | no_relation     | no_relation        | no_relation | no_relation       |



# Generative approach

Used in current state-of-the-art approaches, technically difficult.

**Idea:** train seq2seq model to generate one or more relation tuples (subject, relation, object) for a given input sentence.



# Relevant Literature

- Pere-Lluís Huguet Cabot and Roberto Navigli. 2021.  
[REBEL: Relation Extraction By End-to-end Language generation.](#)  
*In Findings of the Association for Computational Linguistics: EMNLP 2021.*
- Jue Wang and Wei Lu. 2020.  
[Two are Better than One: Joint Entity and Relation Extraction with Table-Sequence Encoders.](#)  
*In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP).*

# Submission

# What you will receive

- We will provide you with a folder organized as follows (some files are omitted):

- nlp2023-hw3/
  - data/
  - hw3/
    - model.py
    - **stud/**
  - **model/**
  - **requirements.txt**
  - test.sh

- You are allowed to edit only the items in bold!

# What you will receive

- We will evaluate your work using Docker
  - You should be fine even if you don't know anything about it
- If **test.sh** runs on your side, it will run on ours as well
  - Just keep in mind: do not change any file but those we marked in bold as editable in the previous slide
- Additionally, we wrote a **README.md** to get you everything up and running
- You can find the code repository [here](#)!

# What we expect from you

- The zip folder we gave you (but populated :))
- Put your training code (if you used Colab, download the notebook .ipynb and place it) in **hw3/stud/**
- If you use any additional library, modify the **requirements.txt** file as needed (click [here](#) for info)
- Use the data (train, dev and test) in the data folder
  - use each file as defined in the **standard ML conventions** (*train for training, dev for model selection and test for final testing of the model*)

# What we expect from you

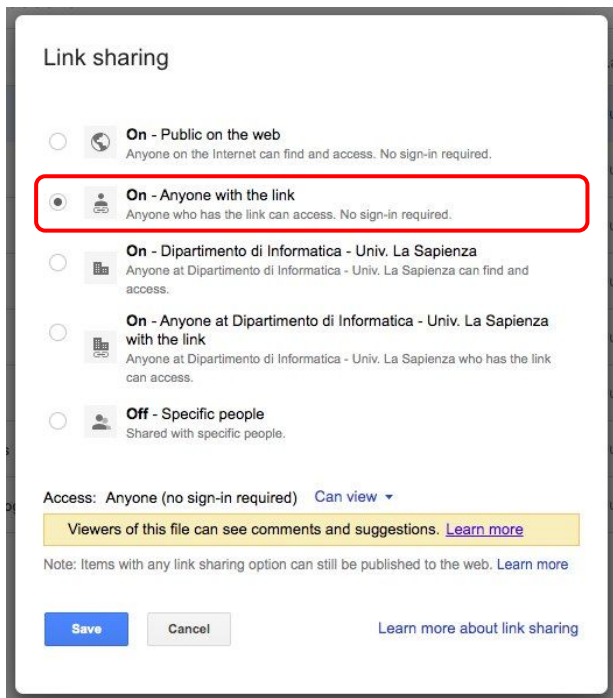
- Put everything your model needs (vocabulary, weights, ...) inside the **model/** folder, and be sure to properly load them in your model
- In **hw3/stud/implementation.py** implement the **StudentModel** class
  - Load your model and use it in the **predict** method
  - You must respect the signature of the predict method!
  - You can add other methods (i.e. the constructor)
- In **hw3/stud/implementation.py** implement the **build\_model** function
  - It should initialize your **StudentModel** class.

# What we expect from you

- Use **test.sh** to check that everything works
- Add your **report.pdf** to the folder (yes, export it in PDF even if you are using Word!)
- Name the zip folder **lastname\_studentid\_hw3.zip**:
  - Ex: Luigi D'Andrea will submit a file named **dandrea\_1234567\_hw3.zip**
  - If you are unsure which name to put, use the one in your institutional email account



# Submission Instructions



The screenshot shows the 'Link sharing' settings in Google Drive. The 'On - Anyone with the link' option is selected and highlighted with a red rectangle. Below it, the 'Access' is set to 'Anyone (no sign-in required)'. A yellow banner indicates that viewers can see comments and suggestions. At the bottom, there are 'Save' and 'Cancel' buttons, and a link to 'Learn more about link sharing'.

Link sharing

☐ On - Public on the web  
Anyone on the Internet can find and access. No sign-in required.

☒ On - Anyone with the link  
Anyone who has the link can access. No sign-in required.

☐ On - Dipartimento di Informatica - Univ. La Sapienza  
Anyone at Dipartimento di Informatica - Univ. La Sapienza can find and access.

☐ On - Anyone at Dipartimento di Informatica - Univ. La Sapienza with the link  
Anyone at Dipartimento di Informatica - Univ. La Sapienza who has the link can access.

☐ Off - Specific people  
Shared with specific people.

Access: Anyone (no sign-in required) [Can view](#)

Viewers of this file can see comments and suggestions. [Learn more](#)

Note: Items with any link sharing option can still be published to the web. [Learn more](#)

[Save](#) [Cancel](#) [Learn more about link sharing](#)

- Upload the zip on your **institutional** Drive and make it **link-shareable** and **public** to anyone (an automatic script will download it).
- Make sure it is accessible via an incognito page of your browser!
- Do **NOT modify** the folder structure
- You have to submit the homework through the [submission form](#) on Google Classroom. You will be asked to fill a form with the requested information and the **link** to the zip you uploaded on Drive.

# Evaluation

# Evaluation

- Use the **validation split** to select the **best model/hyperparameters** configuration
- Use the **test split** to evaluate your model and **estimate its performance**
- The final evaluation will be conducted on a **SECRET** test set
- The evaluation metric will be the **micro F1-score** obtained comparing your model's predictions with our golden labels
- **Strict evaluation:** a relation is considered correct only if the **subject and object entity spans are correctly extracted** and the **relation type is correctly classified** (i.e., fully overlap with the annotation).

# Evaluation

## Micro-F1 explanation

The **micro F1-score** is defined as:

$$F_1 = 2 \cdot \frac{\text{recall} \times \text{precision}}{\text{recall} + \text{precision}}$$

$$\text{precision} = \frac{\text{“number of predictions that overlap with the gold annotations”}}{\text{“number of predictions”}}$$

$$\text{recall} = \frac{\text{“number of predictions that overlap with the gold annotations”}}{\text{“number of gold annotations”}}$$

# Evaluation

## Micro-F1 example

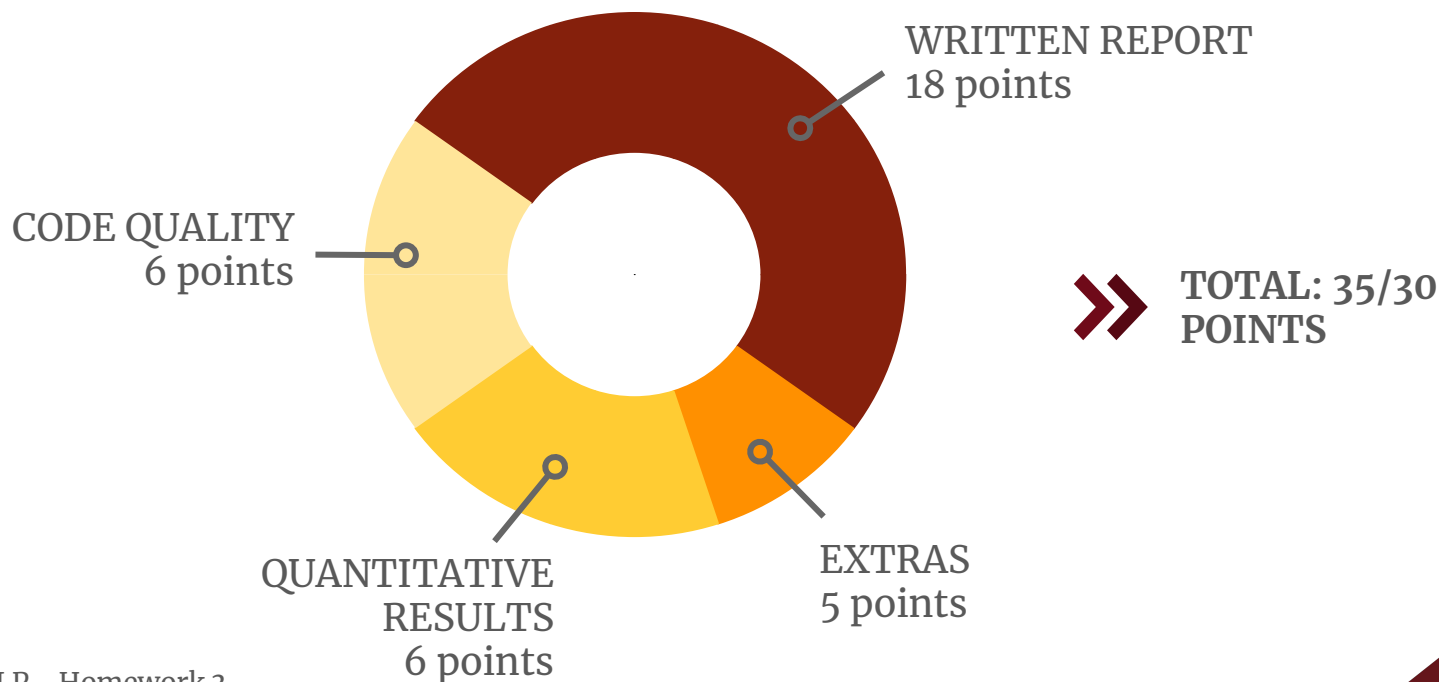
```
{
  "tokens": ["Joe", "works", "at", "Apple", "in", "Cupertino"],
  "relations": [
    {"subject": {"start_idx": 0, "end_idx": 1, "entity_type": "PER", "text": "Joe"},
    "relation": "employed-at",
    "object": {"start_idx": 3, "end_idx": 4, "entity_type": "ORG", "text": "Apple"}},
    {"subject": {"start_idx": 3, "end_idx": 4, "entity_type": "ORG", "text": "Apple"},
    "relation": "employer",
    "object": {"start_idx": 0, "end_idx": 1, "entity_type": "PER", "text": "Joe"}},
    {"subject": {"start_idx": 3, "end_idx": 4, "entity_type": "ORG", "text": "Apple"},
    "relation": "located-in",
    "object": {"start_idx": 5, "end_idx": 6, "entity_type": "LOC", "text": "Cupertino"}}],
  "predictions": [
    {"subject": {"start_idx": 0, "end_idx": 1, "entity_type": "PER", "text": "Joe"},
    "relation": "employed-at",
    "object": {"start_idx": 2, "end_idx": 4, "entity_type": "ORG", "text": "at Apple"}},
    {"subject": {"start_idx": 3, "end_idx": 4, "entity_type": "ORG", "text": "Apple"},
    "relation": "located-in",
    "object": {"start_idx": 5, "end_idx": 6, "entity_type": "LOC", "text": "Cupertino"}}],
}
```

Number of predictions that overlap with gold annotations: 1

Precision:  $\frac{1}{2} = 0.5$       Recall:  $\frac{1}{3} \approx 0.33$       F1: 0.40

# Evaluation

We will take into account the following criteria:



# Report: dos and don'ts

- **ACL 2023 paper template**
  - Freely available: [LaTeX](#), [Word](#) or [Overleaf](#)
  - You can use either the LaTeX or the Word template, your choice
  - **DO NOT MODIFY** the template (margins, spacing, font size)
  - Use the non-anonymous flag, so you can enter your name
- **Max 2 pages**
  - For the report, including title, subtitles, etc.
  - This is a **STRICT RULE!**
- **Unlimited extra pages for images, tables and references**
  - Every image and table must have a caption (don't abuse them please :) )
  - Tables and images must be referenced in the report

# Report: what you are expected to do



We expect a good report to be:

- **Readable and understandable**
  - We will not give penalties for English errors, but we expect the report to follow a clear flow. We don't want to read just a sequence of statements on what you did without showing the reasoning behind your choices
- **Well-structured and organized**
  - Take inspiration from the many papers available online and organize your report in well-defined sections (e.g. method, setup, experiments, results...)



# Report: what you are not expected to do



We expect a good report **NOT** to include:

- Unnecessary **task** or **dataset descriptions**
  - just focus on your solution to the problem
- **Code** copy-paste
  - Your code should be self-explanatory, so no need to show it in the report. You can add **pseudocode** to show some particular algorithm, but **no code or screenshots**, please!

# Report: what you are not expected to do



We expect a good report **NOT** to include:

- **Unnecessary low-level implementation details**
  - Avoid any **low-level implementation/technical details** like “I used a dictionary to store these values”, “I had to use configuration X to solve this exception”, “I could not use Y because there was a dependency issue with Z”, etc.
  - Instead, **we are interested in high-level abstractions/strategies** you decide to use to tackle the homework, as well as the **intuitions behind your choices**.  
E.g. use and description of a particular model, explanation of how and why an architecture works, etc.

# Application: what you are expected to do



Your project should conform to the following rules:

- You **MUST** use PyTorch.
  - TensorFlow and other deep learning frameworks are **NOT** allowed.
  - PyTorch Lightning is allowed and suggested.
  - HuggingFace Transformers is allowed and suggested.
- Libraries (such as tqdm, sklearn, NLTK) are fine, but since the line between a framework and a library is sometimes blurred, please ask in the Google Classroom group before using any external library: **any other** library and framework **MUST be agreed with the TAs**.

# Application: what you are not expected to do



Your project should conform to the following rules:

- **You are not allowed** to use tools/architectures that have not been explained yet in the course, in particular:
  - word embeddings (Word2Vec, GloVe, etc.) **are allowed**,
  - contextualized word embeddings (ELMo, etc.) **are allowed**,
  - Transformer-based models (BERT, BART, RoBERTa, etc.) **are allowed and suggested**.
- For any doubt, please ask the TAs on Google Classroom.
- **Comment** your code, please!

# Quantitative Results

We will evaluate the **performance of your model** on a SECRET test set.

You can get **from 0 to 6** points according to the following **thresholds**:

- $F1 < 0.25$   $\Rightarrow$  FAIL
- $0.25 < F1 < 0.40$   $\Rightarrow$  0
- $0.40 < F1 < T2$   $\Rightarrow$  1
- $T2 < F1 < T3$   $\Rightarrow$  2
- $T3 < F1 < T4$   $\Rightarrow$  3
- $T4 < F1 < T5$   $\Rightarrow$  4
- $T5 < F1 < T6$   $\Rightarrow$  5
- $F1 > T6$   $\Rightarrow$  6

# Quantitative Results

We will evaluate the **performance of your model** on a SECRET test set.

You can get **from 0 to 6** points according to the following **thresholds**:

- $F1 < 0.25$   $\Rightarrow$  FAIL
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- $T2 < F1 < T3$   $\Rightarrow$  2
- $T3 < F1 < T4$   $\Rightarrow$  3
- $T4 < F1 < T5$   $\Rightarrow$  4
- $T5 < F1 < T6$   $\Rightarrow$  5
- $F1 > T6$   $\Rightarrow$  6

Thresholds will be defined  
based on an internal reference  
model and the **normalized  
distribution of YOUR scores!**

# Extras

You can achieve **up to 5 points with some extras!**

An “extra” is whatever you decide to add to your model to make it better. For instance:

- Comparative analysis of results from different approaches
- Informative plots in your report
- **Generative approaches** (e.g. using seq2seq models like BART)
- **New ideas** (including using other approaches in a clever way)

and more, according to internal baselines. Don't forget to **explain your choices** in the report! Extras that are not explained in the report will not be considered for evaluation.

# Evaluation

- `test.sh` is identical to what we will be using
- **If it does not run on your side, we will not correct your homework**
- Note that, if you use **any kind of hard-coded paths**, this script won't work
- Use [paths relative](#) to the project root folder, e.g.:
  - **NO:** `/home/pincopallino/my_folder/model/weights.pt`
  - **OK:** `model/weights.pt`



# Warnings

Things you should be aware of



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# Please be aware that

This is an **individual exercise**! Collaboration among the students is **not** allowed.

We will check for **plagiarism** both manually and automatically.

It is **not allowed** to:

- Copy from other students.
- Share your code with other students.
- Use ChatGPT or similar systems for report writing.
- Copy from online resources (StackOverflow, GitHub, Medium, Kaggle and so on).

You are also allowed to use the **SOME** parts of the presented class notebooks. However, you **MUST** explicitly specify these parts in your code comments.

# Data policy

- For your experiments, use **ONLY** the provided data (train, dev and test) in the data folder; use each file as defined in the standard ML conventions (train for training, dev for model selection and test for testing).
- If you train it on dev or test set, it will be a **FAIL**.

# Tips



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# A few tips to organize your work:

- **Start as soon as possible!**
  - Training a neural network requires time, possibly hours, depending on your hardware
- **Start small!**
  - If you don't get decent results with a very simple neural network, there is a good chance that adding other things won't make your model perform better
- **Leave some time for hyperparameter tuning!**
  - Sometimes good hyperparameter combinations can do wonders for your neural network
- **Use Google [Colab](#) (free GPUs!)**

# Deadline

When to deliver what



# Deadline

The students **who passed the first homework** may deliver the third one in one of the four available deadlines (2023):

1. Early submission: May 31st (23:59 AoE) → only this date allows late submission!  
**Late submission: June 2th (23:59 CEST)**  
Presentation: 5th June, 8.30 (up to 12 minutes)
2. Submission: June 28th (23:59 AoE)  
Presentation: July 5th, 8.30(up to 12 minutes)
3. If particularly well deserved (e.g. bonus and/or involvement),  
**secret submission deadline: July 17-ish (23:59 AoE)**  
Presentation: July 24-ish, 9.00(up to 12 minutes)
4. Submission: September 5th (23:59 AoE)  
Presentation: September 13th, 8.30(up to 12 minutes)

# Awards

Get a Sapienza NLP™ t-shirt



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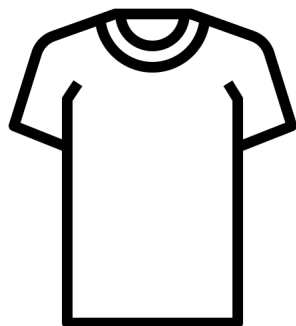




# Win a Sapienza NLP t-shirt!

We will hand out amazing Sapienza NLP t-shirts to the **overall top-5** students!

The final ranking will be computed according to the scores on our **secret** test set.



# That's not all

If your work is novel, interesting and original, we will gladly invite you to work together with us to extend on a fully-fledged paper for **TOP-TIER INTERNATIONAL CONFERENCE!**

Just over the last 12 months, the Sapienza NLP group published more than a dozen of papers!

# Questions?

If you have a question that may interest your colleagues, **please ask it on Google Classroom.**

Otherwise, for personal or other questions, email **ALL** of us (but please, only reach for things that can't be asked on the Google Classroom).

Our emails are:

{bonomo, ghonim, martinelli, molfese, perrella, lproietti}@diag.uniroma1.it

Good Luck!!

