



The Augmented Social Scientist

Tips & Tricks

SICSS-Paris, June 2023



Using an LLM to Annotate Text

Using a supervised machine learning algorithm to automatically annotate text is easy

But there are pitfalls you'd better avoid, and best practices

⇒ Last moment of this tutorial = a few tips and tricks

1. **Defining Categories to Annotate**
2. **Creating an appropriate test set**
3. **Designing a Training Strategy**
4. **Active Learning**
5. **“What can I do if I have bad validation scores?”**



1. Defining Categories



1. Defining Categories

You want to train an LLM to annotate automatically some text for you.

How do you decide on the categories you want to use?

- **Theory:** any category you deem relevant
- **Practice:** more complex, and depends on a set of parameters



1. Defining Categories

1. Design a temporary coding scheme



1. Defining Categories

1. Design a temporary coding scheme
2. Annotate a small (10-100) units of text, sampled at random
3. Revise coding scheme and annotate again



1. Defining Categories

1. Design a temporary coding scheme
2. Annotate a small (10-100) units of text, sampled at random
3. Revise coding scheme and annotate again
 - a. Pause: Is it working? Note down issues, hesitations (w/ examples)



1. Defining Categories

1. Design a temporary coding scheme
2. Annotate a small (10-100) units of text, sampled at random
3. Revise coding scheme and annotate again

Are you happy with your coding scheme?

- **No:** Start over
- **Yes:** Continue annotating + write detailed guidelines



1. Defining Categories

Question: How refined can my categories be?



1. Defining Categories

Question: How refined can my categories be?

- “It depends on the data”, but
 - Do not limit yourself to the obvious (go for semantics, not lexicon)
 - Do not expect an algorithm to do better than a skilled human

⇒ TRY!

(And ask yourself: could you easily convey the idea to a colleague?)



1. Defining Categories

Question: What is the correct unit of analysis?



1. Defining Categories

Question: What is the correct unit of analysis?

- “It depends on the data”, but
 - A sentence is an obvious candidate, but you will lose lots of context



1. Defining Categories

Question: What is the correct unit of analysis?

- “It depends on the data”, but
 - A sentence is an obvious candidate, but you will lose context
 - A paragraph is a second obvious candidate, but
 - You do not always have paragraphs clearly delimited
 - It will take more examples to train a model



1. Defining Categories

Question: What is the correct unit of analysis?

- “It depends on the data”, but
 - A sentence is an obvious candidate, but you will lose context
 - A paragraph is a second obvious candidate, but
 - A longer text then seems great, but
 - It will take many more examples to train a model
 - The models “stop” reading after a few hundreds tokens



1. Defining Categories

Question: One multi-class classifier, or several binary classifiers?



1. Defining Categories

Question: One multi-class classifier, or several binary classifiers?

- “It depends on the data”, but
 - Binary models will be easier to train
 - If you do a lot of binary classifiers instead of a multiclass,
 - You will get more refined...
 - Or more ambivalent results



1. Defining Categories

Question: How much should you annotate?

- “It depends on the data”, but
 - A binary classifier could only need a few dozen examples



1. Defining Categories

Question: How much should you annotate?

- “It depends on the data”, but
 - A binary classifier could only need a few dozen examples
 - Annotation is intellectually healthy



1. Defining Categories

Question: How much should you annotate?

- “It depends on the data”, but
 - A binary classifier could only need a few dozen examples
 - Annotation is intellectually healthy
 - There are shortcuts to save massive amounts of time (“active learning”)
 - If your simple classifier does not work after 8h of annotation, reconsider



2. Creating an appropriate test set

- Should be representative of the corpus
- No intersection with the training set
- Double check it!



3. Training strategy

- Training parameters



3. Training strategy

- Training parameters
 - Learning rate (lr)



3. Training strategy

- Training parameters
 - Learning rate (lr)
 - Number of epochs (n_epochs)



3. Training strategy

- Training parameters
 - Learning rate (lr)
 - Number of epochs (n_epochs)
- Training set (downsampling/oversampling)



3. Training strategy

What to remember

1. No general rules, you need to try
2. No need to spend too much time



4. Active learning

A very common problem: unbalanced dataset

e.g. 10% positive, 90% negative

Objective: obtain 300 positive sentences for training

- If random sampling -> manual annotation of 3000 sentences
- How to obtain more positive samples with less manual annotation?



4. Active learning

Active learning: use intermediate models to find more positive samples

- How does it work?



4. Active learning

Active learning: use intermediate models to find more positive samples

- How does it work?

2 strategies of active learning

- Most probable (max probability)
- Most ambiguous (max entropy)



4. Active learning

Active learning: use intermediate models to find more positive samples

- How does it work?

2 strategies of active learning

- Most probable (max probability)
- Most ambiguous (max entropy)



Hold-out (representative) test set



5. What to do if you have bad validation scores

- Double check (again) the test set
- Add training data
- Read some model predictions to understand



Conclusion

- Diving into new sources of data
- With your own research questions + tagging scheme

Resources:

- Package: [https://github.com/rubingshen/Replication Augmented](https://github.com/rubingshen/Replication-Augmented)
- [Article \(SMR, 2022\)](#)
- [Google Colab tutorial](#)