jambit CoffeeTalks, 6. März 2020

Aspect-based Sentiment Analysis with PyTorch

(oder: Wie man Sentiment mit PyTorch analysieren kann)

Wiltrud Kessler

Outline

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Motivation

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1,973 customer reviews

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1,734 customer reviews

Automatically analyze reviews

- We want to automatically analyze reviews.
- We don't want to write lots of rules manually.

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$\Rightarrow$ Machine Learning

- Let the computer learn the rules from the data.
- The computer can then apply the learned rules to new data.

Sentiment Analysis

Sentiment and sentiment polarity [Liu 2015]

An opinion (*sentiment expression*) is a subjective value statement about an entity. *Sentiment polarity* is the "direction" of the judgment that an opinion expresses.

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An opinion (*sentiment expression*) is a subjective value statement about an entity. *Sentiment polarity* is the "direction" of the judgment that an opinion expresses.

The Bagels have an outstanding taste. `(positive)`

It is very overpriced and not very tasty . `(negative)`

The problem with star ratings

Aspect-based Sentiment Analysis

Sentiment target and aspects [Liu 2015]

Sentiment does not only have a polarity, but it is also expressed with respect to some *target*, a particular entity or some *aspect* of it.

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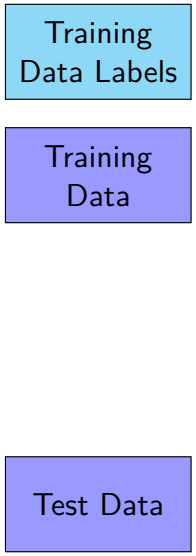
The staff is courteous and friendly . `(service)`

All of the pizzas are terrific `(food)`
and the price is even better ! `(price)`

Also very expensive . `(price)`

Outline

Machine Learning general concept



Sentences from reviews with sentiment aspect labels

Supervised Machine Learning

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  a typical task for Supervised Machine Learning.
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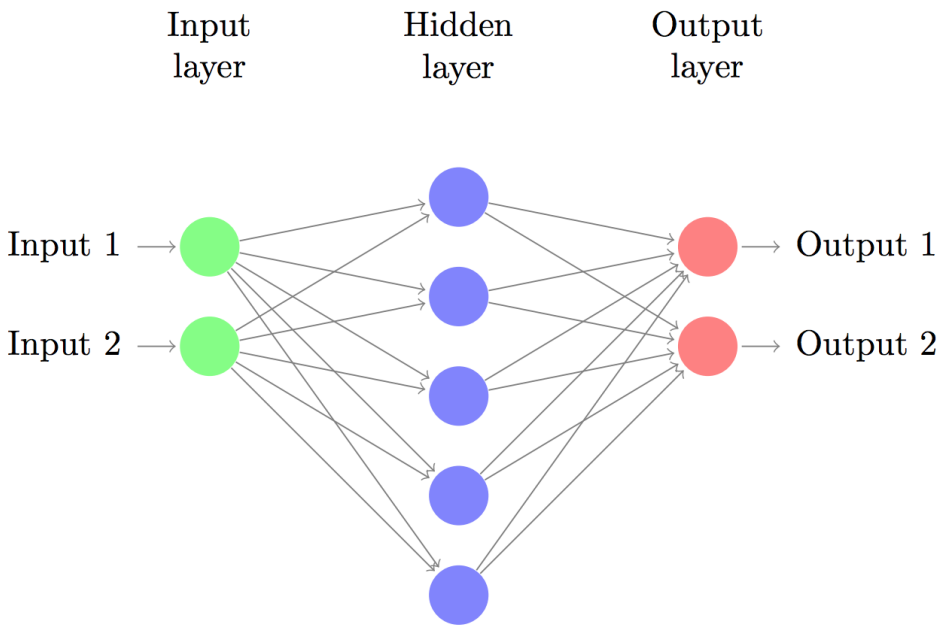
- We have defined a classification problem,
  a typical task for Supervised Machine Learning.
- There are a large number of algorithms for classification.
- We use Deep Learning for this example, specifically a
  Recurrent Neural Network (RNN).
- To understand the task, it is enough to think of a black box:
  We put in training data and get out a model,
  which we can then apply to new data.
- But for those who want to know more . . .

(Artificial) Neural Network

- An artificial neuron calculates a weighted output from inputs.



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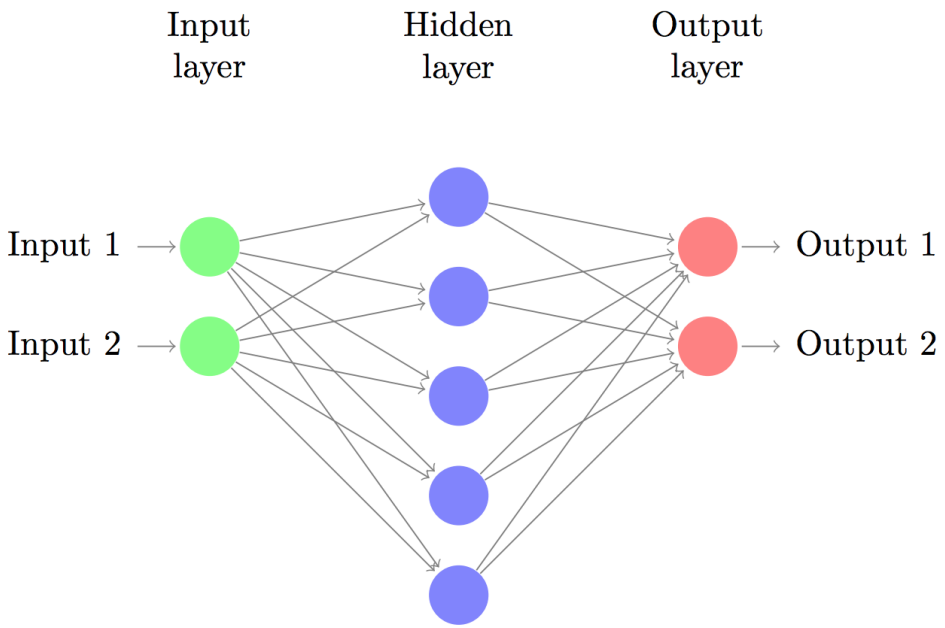
- We can combine several neurons in layers to form a network.



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(Artificial) Neural Network

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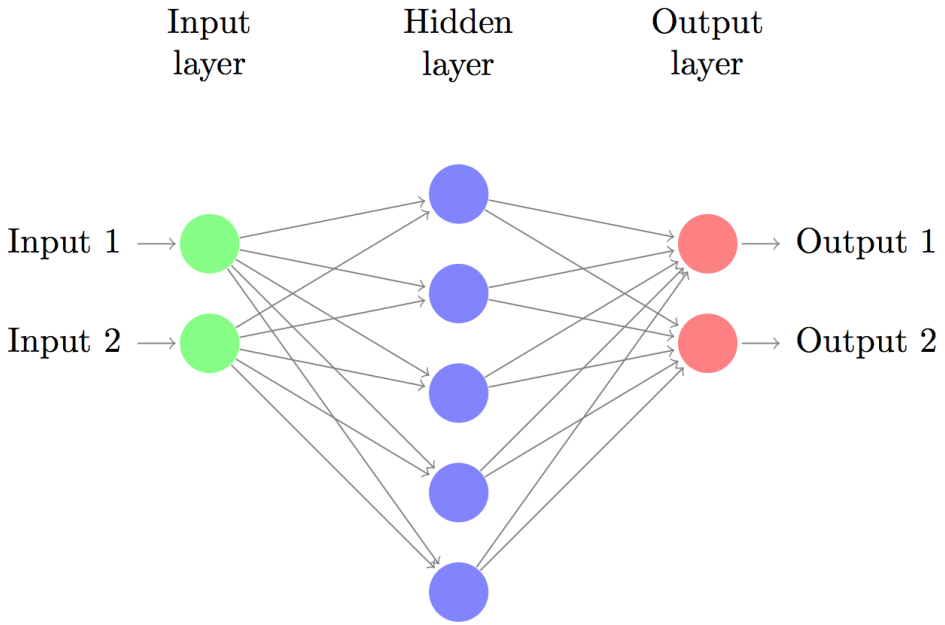
- We can combine several neurons in layers to form a network.
- Deep learning uses more layers than traditional networks.



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Recurrent Neural Network

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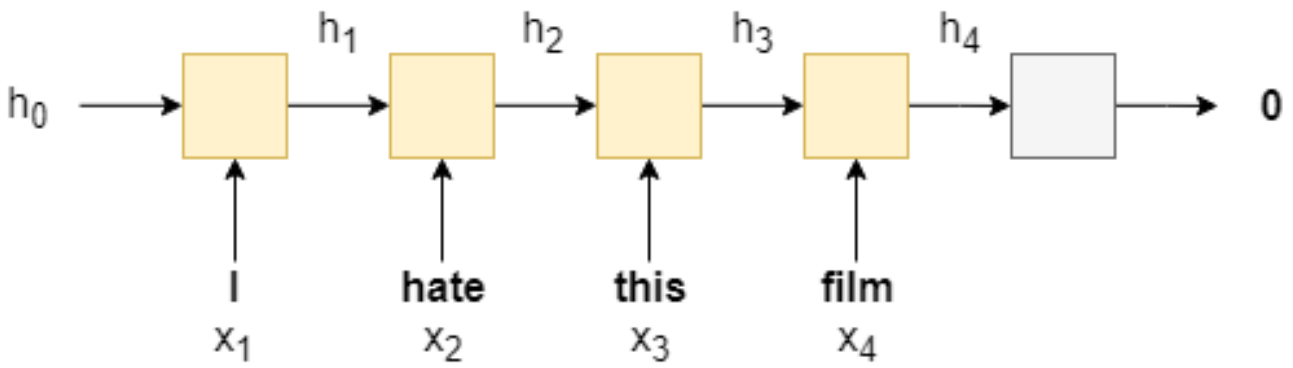
- It performs the same task for every element of a sequence.



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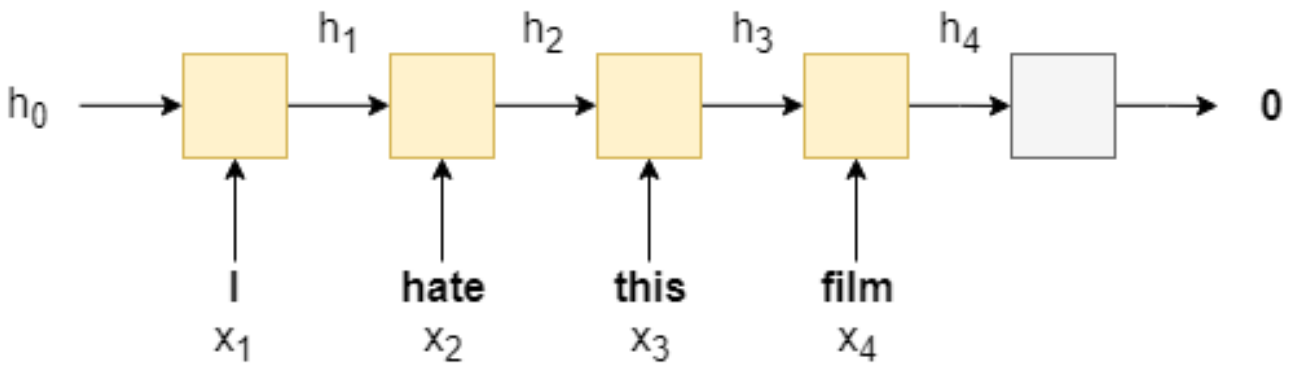
Recurrent Neural Network

- A Recurrent Neural Network (RNN) works on a sequence.
- It performs the same task for every element of a sequence.
- The output at step i is dependent on the new input x_i and the previous computations h_{i-1} (hidden state).
- Last is a linear layer to produce a prediction.



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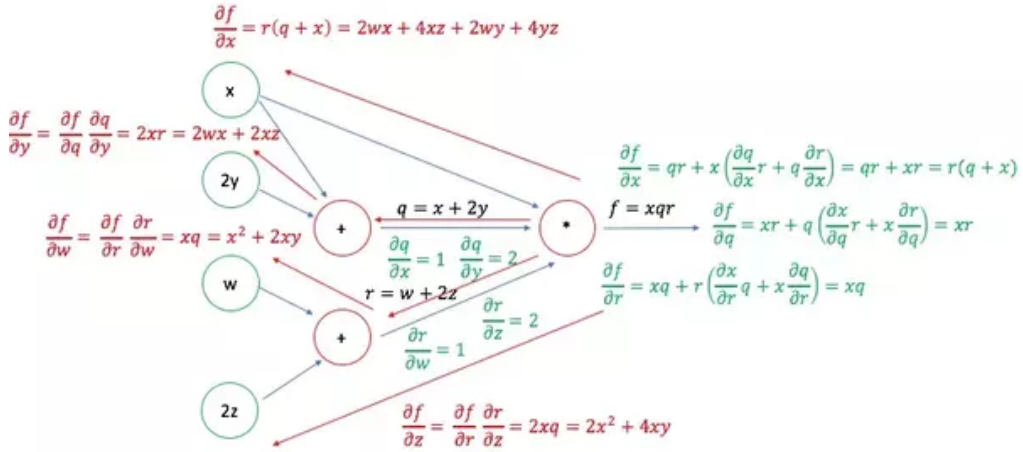
Training a Neural Network

- Training iterates through all examples in the training data.
- Compare a prediction to the actual label and measure how much the network got wrong (calculate loss).
- Adapt the weights of the network so that the prediction would come out better (optimization).



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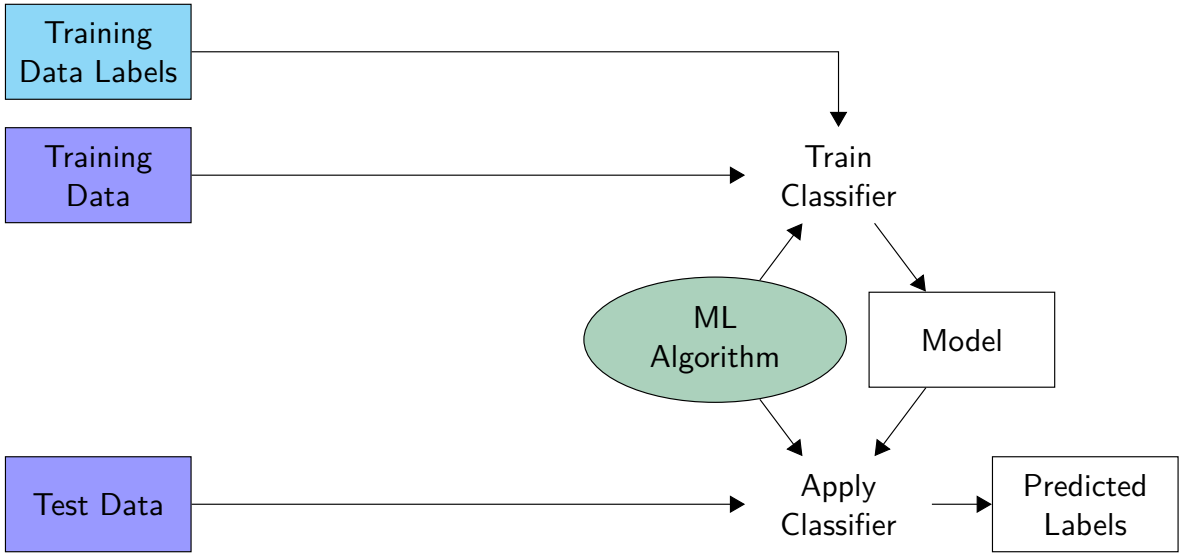
Machine Learning general concept



Sentences from reviews with sentiment aspect labels

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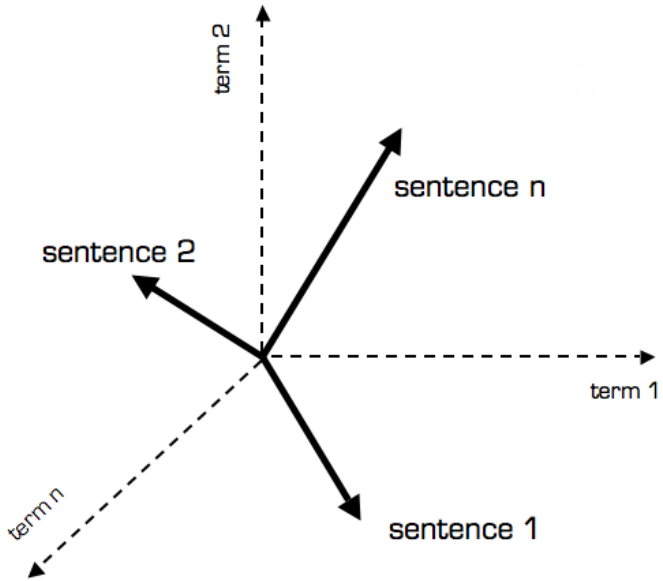
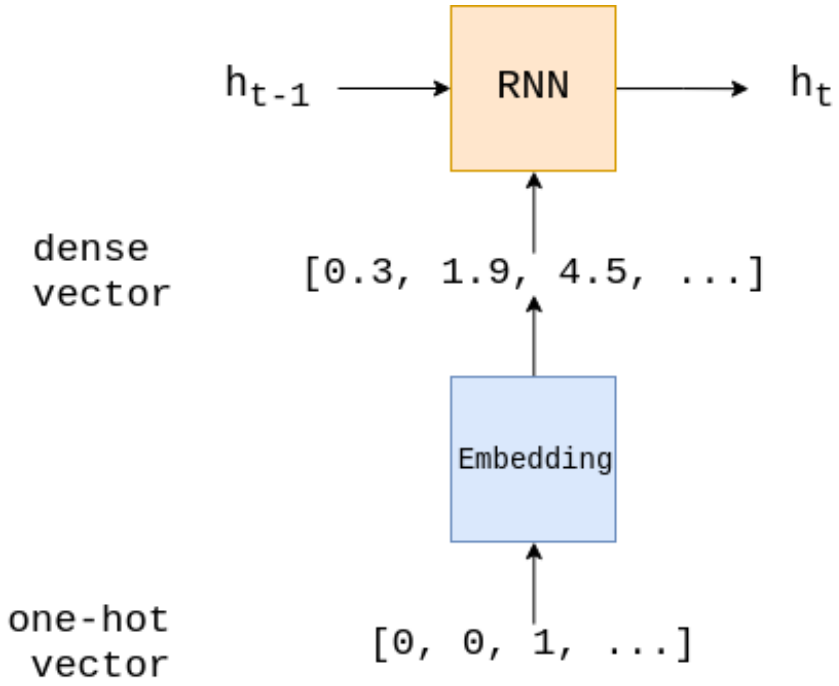
  - The same representation for:
    John loves Mary.
    Mary loves John.
    Loves John Mary?
- Main idea 2: Vector Space Model
  - Every word is a dimension.
  - Every text is a vector.
  - An vector entry is 1 if a word occurs in the text, 0 otherwise.



Word embeddings

- A word embedding transforms a vector with lots of 0/1 dimensions to a dense vector with less dimensions.
- Words with similar meaning lie close together.



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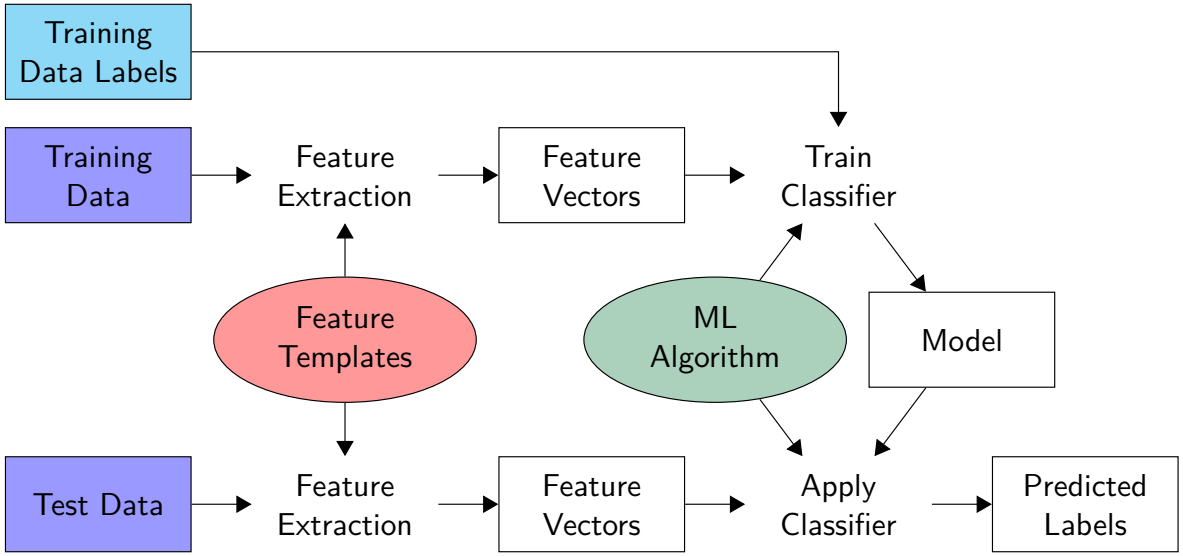

Sentences from reviews with sentiment aspect labels
Recurrent Neural Network with bag of words/vector space features

Evaluation

- How do we know if our model is good?

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Evaluation

- How do we know if our model is good?
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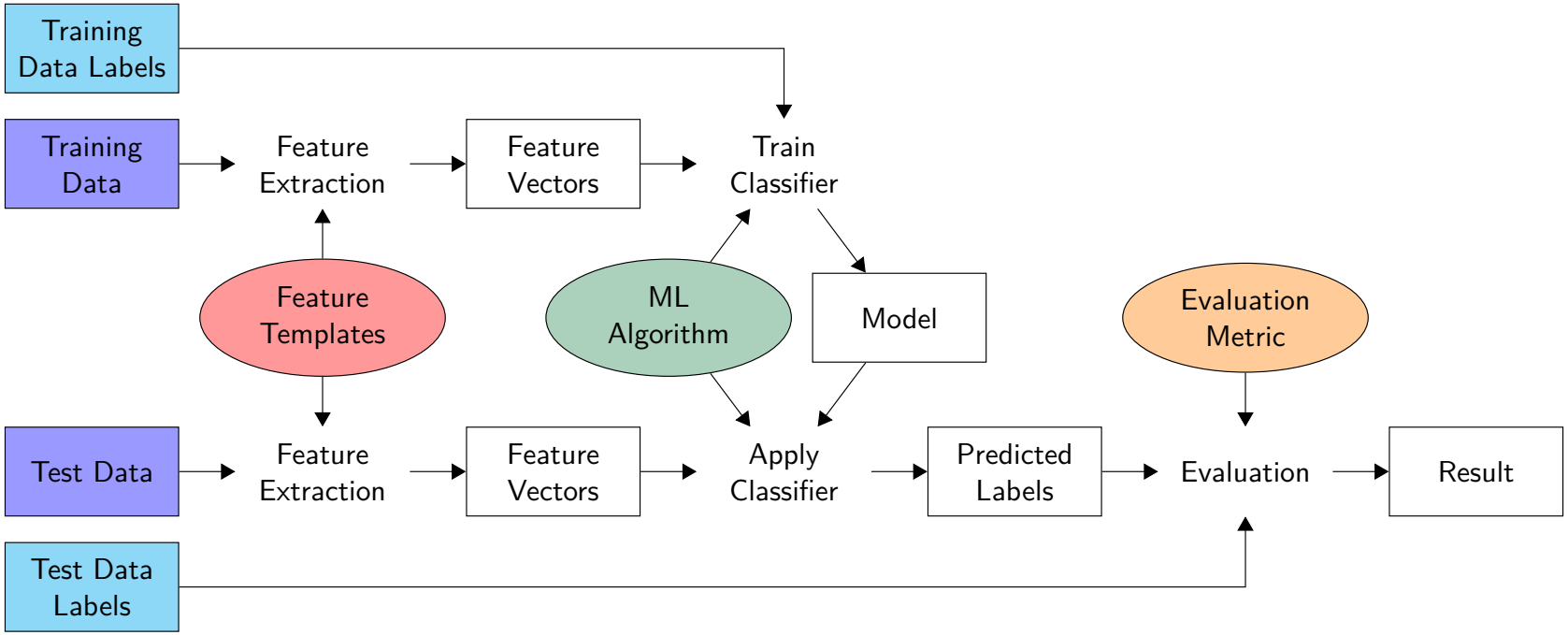
- We measure *Accuracy*, the fraction of classification decisions by our model that are correct.

Machine Learning general concept



Sentences from reviews with sentiment aspect labels
Recurrent Neural Network with bag of words/vector space features
evaluated by Accuracy

Outline

Training and Test Data

- Restaurant data from SemEval 2014 [Pontiki et al. 2014]
- Training set: 3041 sentences, 3713 category annotations

food	1232
service	597
ambience	431
price	321
anecdotes/misc	1132

- Test set: 100 sentences, 114 category annotations

food	41
service	8
ambience	7
price	12
anecdotes/misc	46

Let's code!

[3]
```
import torch
import torch.optim as optim
import torch.nn as nn
import time
```

[4]
```
labeltype = 'term'
polarities = ['1', '-1']
use_aspect_label = True
```

[5]
```
# Load the data from csv

ID = data.Field()
TEXT = data.Field()
ASPECT = data.Field()
POLARITY = data.Field()
LABEL = data.LabelField()

# field ->   sent_id          text         ex_id          aspect           polarity
if use_aspect_label:
  fields = [(None, None), ('text', TEXT), (None, None), ('label', LABEL), (None, None)] # Use aspect as label
else:
  fields = [(None, None), ('text', TEXT), (None, None), (None, None), ('label', LABEL)] # Use polarity as label

prefix = 'semeval2014_restaurants_' + labeltype + "_" + ".".join(polarities)
train_data, valid_data, test_data = data.TabularDataset.splits(
                                    path = '/content/drive/My Drive/semeval',
                                    train = prefix + '_train.csv',
                                    validation = prefix + '_val.csv',
                                    test = prefix + '_test.csv',
                                    format = 'csv',
                                    fields = fields,
                                    skip_header = True
)

print(f'Number of training examples: {len(train_data)}')
print(f'Number of validation examples: {len(valid_data)}')
print(f'Number of testing examples: {len(test_data)}')

print(vars(train_data.examples[0]))
print(vars(valid_data.examples[0]))
print(vars(test_data.examples[0]))
```

```
Number of training examples: 2376
Number of validation examples: 593
Number of testing examples: 86
{'text': ['the', 'first', '2', 'courses', 'were', 'very', 'good', 'but', 'the', 'chocolate', 'sampler', 'was', 'too', 'rich', 'for',
{'text': ['but', 'that', 'was', 'it', 'the', 'icing', 'on', 'the', 'cake', 'a', 'tiramisu', 'that', 'resembled', 'nothing', 'it', 'hi
{'text': ['all', 'the', 'appetizers', 'and', 'salads', 'were', 'fabulous', 'the', 'steak', 'was', 'mouth', 'watering', 'and', 'the',
```

Outline

What about Aspect Terms?

- We have classified sentences as belonging to one of a few categories of aspects.
- But there are many other interesting aspects:
  - Vegetarian food
  - Can pay with credit card
  - Wheelchair accessible
  - Open on Monday
  - ...

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- But there are many other interesting aspects:
  - Vegetarian food
  - Can pay with credit card
  - Wheelchair accessible
  - Open on Monday
  - ...
- We want to identify the actual terms that express the aspect, so that are not limited to a fixed set of aspect categories.

Statistics

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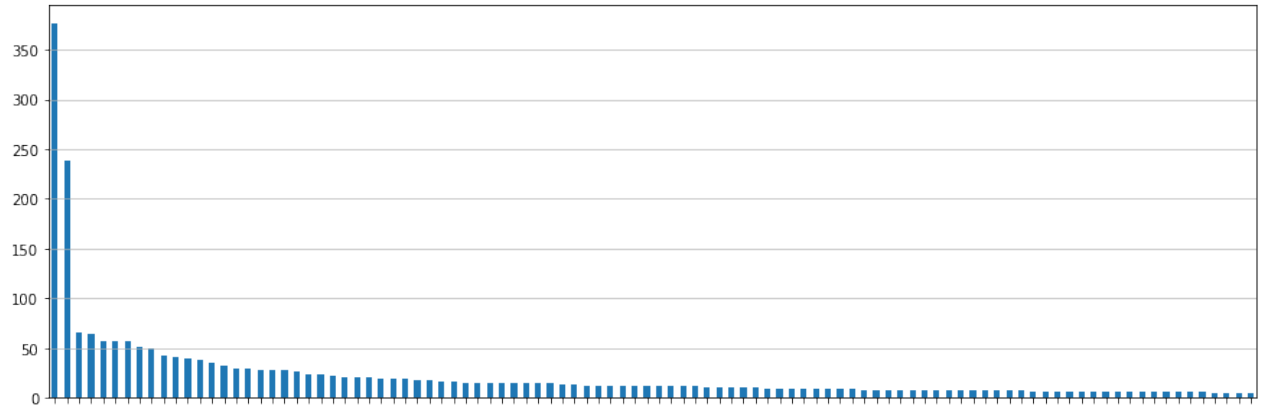
- Training set: 3041 sentences, 3693 aspect term annotations, 721 different aspect terms.
- Most frequent annotated terms in the training set:

food	376	menu	57
service	238	dinner	56
prices	65	pizza	51
place	64	atmosphere	49
staff	57	price	42



Aspect term variations

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- Synonyms:
  bill (15), *check* (6)
- Abbreviations:
  ac (1), *air conditioning* (1)

Aspect term detail

- Aspects can be very detailed:
  - *margarite pizza with cold prosciutto and baby arugula on top*
  - *wild mushroom third generation fornini pizza*
  - *godmother pizza a sort of traditional flat pizza with an olive oil brushed crust and less tomato sauce than usual*

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  - *godmother pizza a sort of traditional flat pizza with an olive oil brushed crust and less tomato sauce than usual*
- Aspects form a fine-grained hierarchy:
  food (376)
  appetizers (4)
  cold appetizer dishes (1), *asian appetizers* (1)
  caprese salad appetizer (1), *guacamole shrimp appetizer* (1)

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Summary and Conclusion

- Sentiment expressions contain much more than just polarity, *aspects* are especially interesting.

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  - Restaurant review sentences
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  - Results are so-so (Accuracy around 30%)
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  - Results are so-so (Accuracy around 30%)
- The task is difficult and we would need more training data and more specific engineering of the network to get a good system.
- Classifying terms instead of categories is even more interesting, but also much more difficult.

Outline

Bibliography I

[Pontiki et al. 2014] M. Pontiki, D. Galanis, J. Pavlopoulos, H. Papageorgiou, I. Androutsopoulos, S. Manandhar (2014). SemEval-2014 Task 4: Aspect Based Sentiment Analysis. Proceedings of the 8th international workshop on semantic evaluation (SemEval 2014). 27-35. `http://alt.qcri.org/semeval2014/task4/`

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Thank you!

Code and slides available at:
`https://github.com/Kaffeedrache/absa_pytorch`

SOFTWARE & SOLUTION DEVELOPER
INNOVATION PARTNER
COFFEE LOVER

Geschäftsführer:
Peter F. Fellinger, Markus Hartinger

Erika-Mann-Straße 63 | 80636 München | +49.89.45 23 47 - 0
Meitnerstraße 8 | 70563 Stuttgart | +49.711.21 95 28 - 0
Klostergasse 3 | 04109 Leipzig | +49.341.22 178 - 0

office@jambit.com
www.jambit.com