Data, Motivation & Objective

Data found on data.bs.ch

- Time series over 10+ years
- month-on-month price increase (mmpi) «Monatsteuerung»,
  year-on-year price increase (yypi) «Jahresteuerung»,
  month and year
- 400+ products, divided into
- 12 main categories

Inspired by our banknote exercise

- Are mmpi and yypi sufficient to explain (classify) the products into the main categories using Deep Learning?
- Spoiler: probably not, because some categories are correlated

The Dataset

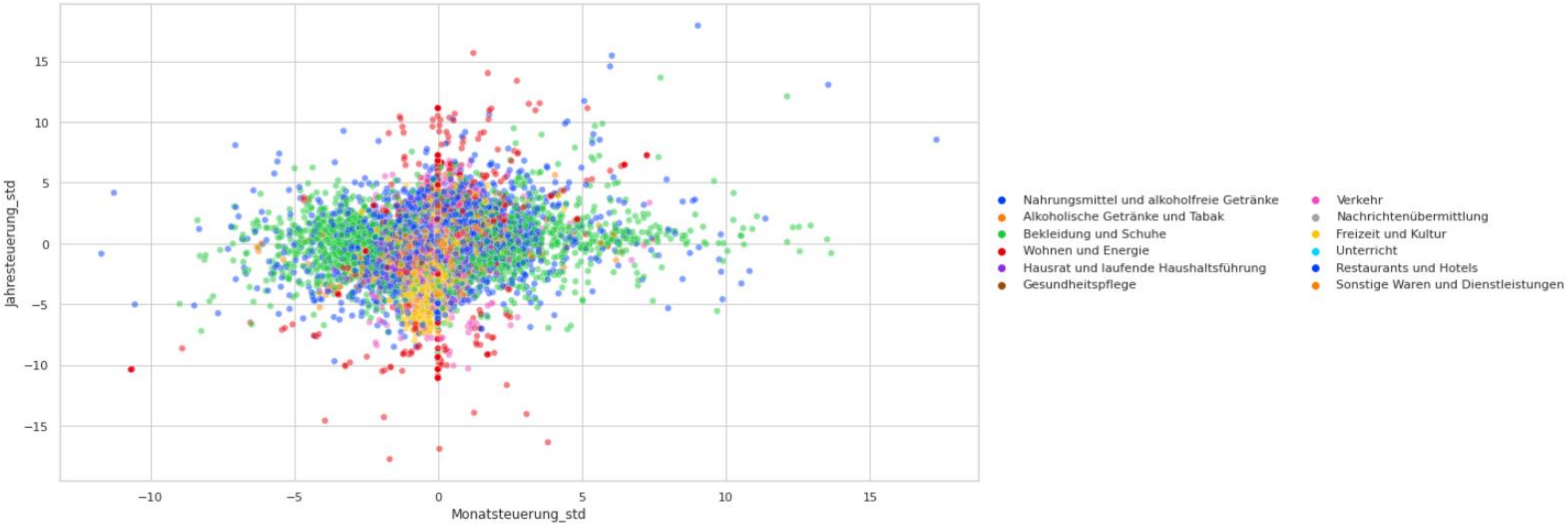
- From 01.01.2009 until 31.12.2019
- 430 products
- 12 main categories (max. 97 prod in ‘Nahrungsmittel’, min. 9 prod in ‘Unterricht’)

Input features:

- Monatsteuerung, Jahresteuerung (z-transformed), Month (cos-transformed)

Label:

- Hauptgruppe (one-hot encoded)



Train - Validation - Test data

Randomly shuffle products: 300 (70%, train), 2 x 65 (15%, validation, test)

→ All index data of a product belong to the same data subset

Our Baseline

Let’s first use “classic” classifiers:

- Multinomial Logistic Regression (using scikit-learn)
- K-nearest Neighbors (using scikit-learn)
- Random guessing

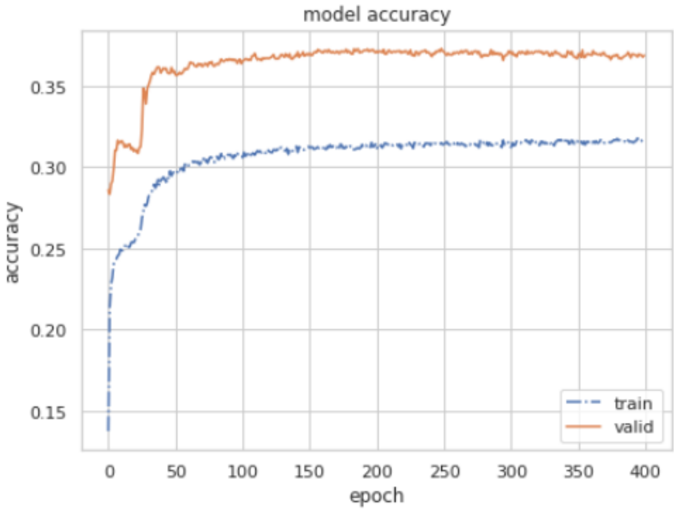
Method	**Accuracy**
LogisticRegression*	28.7%
KNeighborsClassifier*	29.1% (k=10), 35.0% (k=50)
Random	1/12 ~ 8.3%

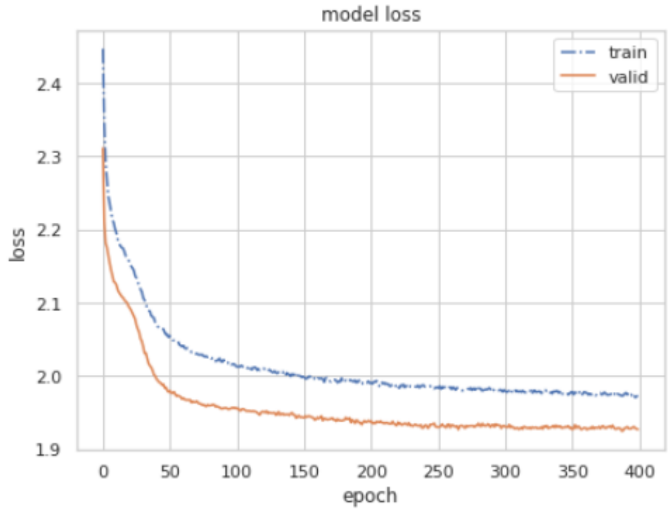
Accuracy of Baseline classifiers (* on *validation data* set)

1st Attempt: predict all 12 classes

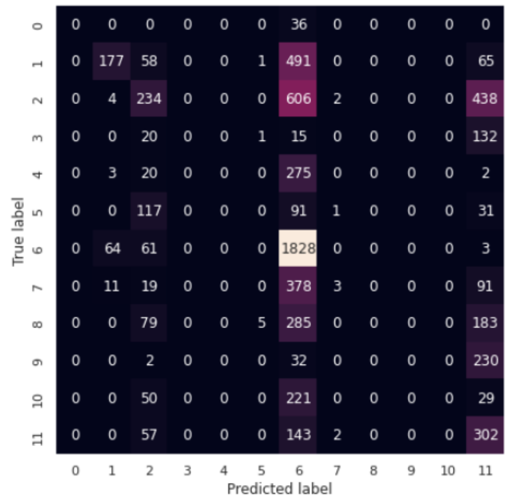
Model : sequential Model, 2 hidden layers + Dropout (0.3), ReLU-activated, softmax-output-layer of size 12, loss: categorical_crossentropy, optimizer: adam, metrics: accuracy

Model performance





Confusion Matrix



That's not what we wanted. Still better than baseline, but…

So, What went wrong?

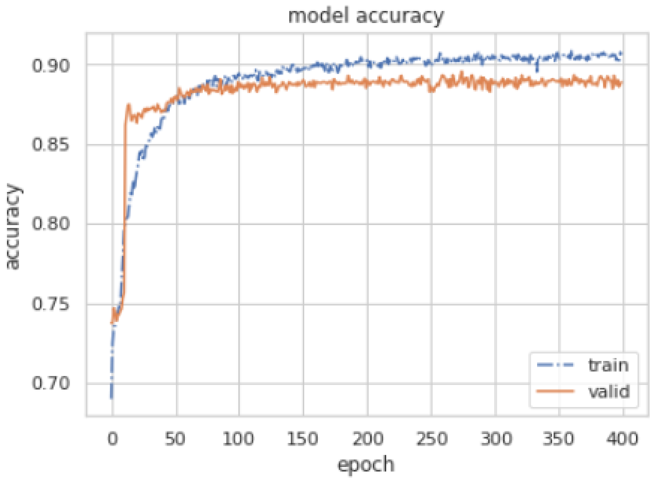
probably too much correlation

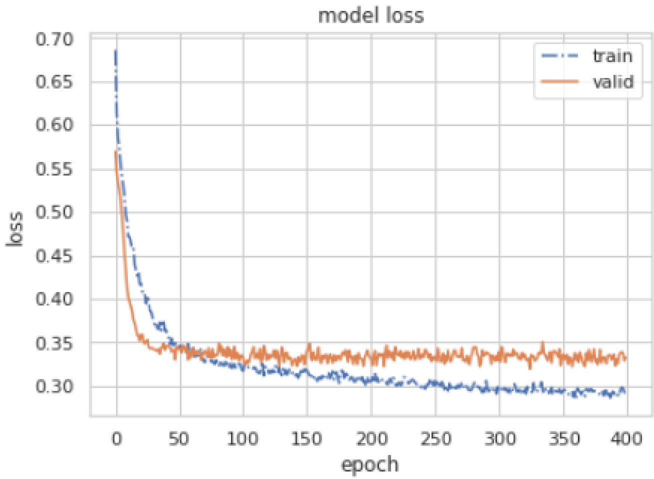
2nd Attempt: predict only 2 classes

Domain knowledge: how about Food vs. Energy?

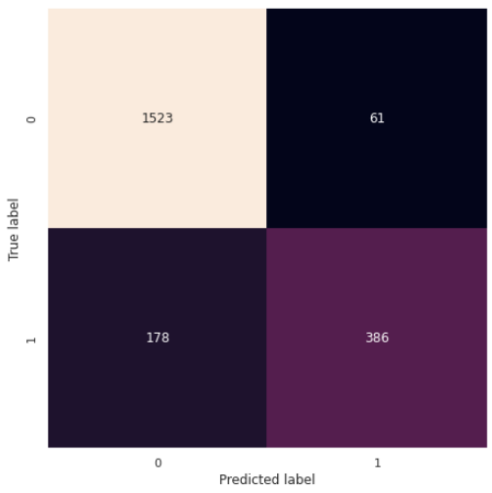
Model: sequential Model, 2 (smaller) hidden layers + Dropout (0.3), ReLU-activated, softmax- output-layer of size 2, loss: categorical_crossentropy, optimizer: adam metrics: accuracy

Model performance





Confusion Matrix



Looks better – but is probably deceiving

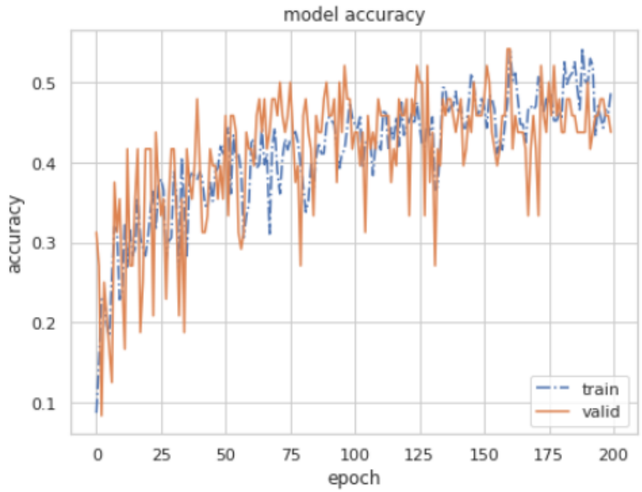
Due to unbalanced class sizes

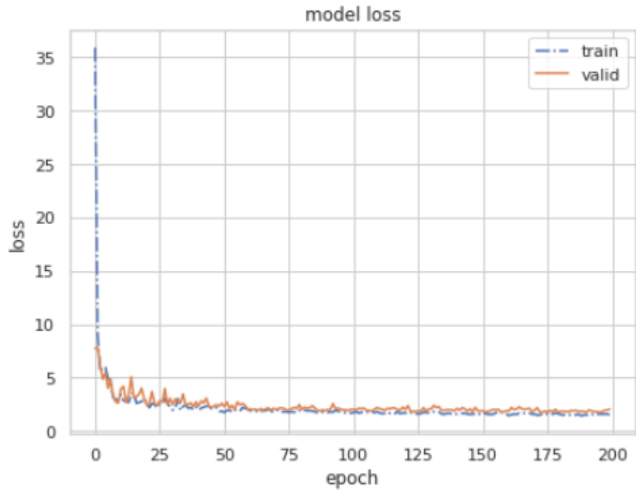
3rd Attempt: Let’s switch axes

use all data of the time series as input features (p=132) (but then… N = 315 obs only)

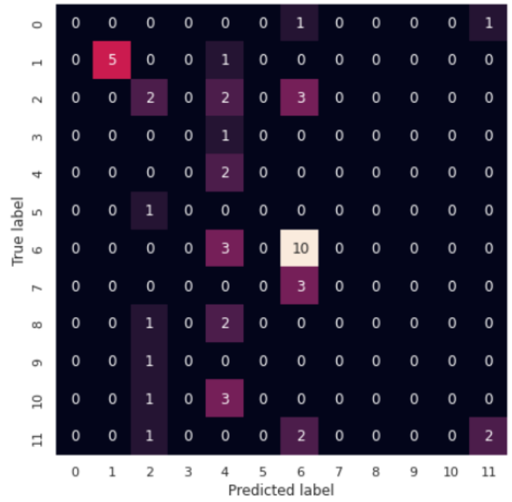
Model: sequential Model, 1 hidden layer, No Dropout, ReLU-activated,
softmax- output-layer of size 12, loss: categorical_crossentropy, optimizer: adam
metrics: accuracy

Model performance





Confusion Matrix



That ain’t any better…

The trained models were either as wiggly as the one depicted, or settled to a stable situation where every observation was then predicted the same label.

Conclusion: Curse of dimensionality, not enough data by a mile.

Lessons learned, Summary & Ideas to go from here

An early mishap we finally detected was that we were not careful enough when doing the one-hot-encoding by using the factorize-method. sort=True helps 😉

The data eluded us quite a bit – or we were a bit too optimistic about what a clever Neural Network could possibly return on input data which is unbalanced and correlated.

So, careful selection of ‘what can be predicted’ is mandatory.

Also clearly visible: having enough data is absolutely key.

While we were working with the data, ideas of other interesting applications with the same data came to our minds: as we’re working with time series, we could use the index prices and make predictions for the future. We’d then employ a 1D Convolutional NN with time dilitation to try to predict possible seasonal trends.

Acknowledgements & References

Thanks to: The Tensorchiefs (https://tensorchiefs.github.io)

Dataset: https://data.bs.ch/explore/dataset/100003/information/

Data Food vs Energy