

Accessible Drought Prediction

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Problem Space

Task:

Predict future drought levels for 1 week to 6 weeks ahead.

Use widely available soil and meteorological data

Our Contribution:

Implementation and utilization of an **Ordinal Classification Estimator** [2]

- Uses simple models for complex predictions

Category	Description
D0	Abnormally Dry
D1	Moderate Drought
D2	Severe Drought
D3	Extreme Drought
D4	Exceptional Drought

Approach

Problem:

- k ordered classes, WLOG call them 1, ... , k

The classifier (ORD):

Turn the problem into k-1 different binary classification problems. For each sample x, y train a model, for each class i, that answers:

is $y > i$?

for $i = 1, \dots, k-1$. Then the predicted class probabilities for the original problem are:

$$\begin{aligned} \Pr[y = 1] &= 1 - \Pr[y > 1], \\ \Pr[y = 2] &= \Pr[y > 1] - \Pr[y > 2], \\ &\vdots \\ \Pr[y = j] &= \Pr[y > j-1] - \Pr[y > j], \\ &\vdots \\ \Pr[y = k] &= \Pr[y > k-1]. \end{aligned}$$

- Can use any binary classifier that can output probability estimates
- Can use a different classifier for each ordinal value

Our base classifier: Logistic Regression

Attempted Approaches

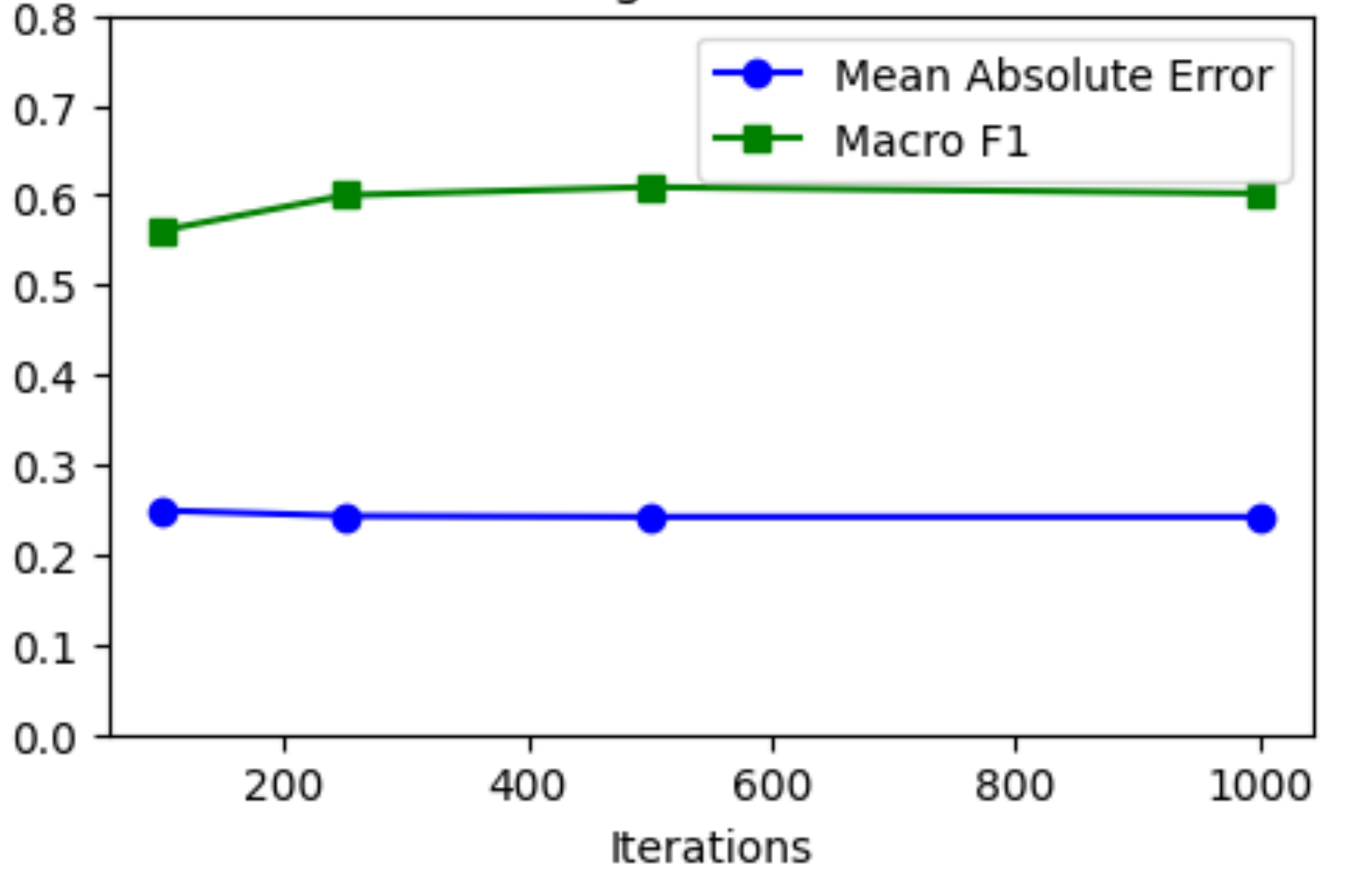
- Multi-layer Perceptron (MLP)
- Boosted Trees

* These approaches did not perform as well due to our computational limits

Results

Model	Macro F1	MAE
LSTM [3]	0.64	0.28
Ridge Regression [1]	0.58	0.26
Ordinal w/ Logistic Regression	0.58	0.20

Performance vs Training Iterations on Validation Data



Convergence Issues

None of the Logistic classifiers ever converged (sci-kit learn: Convergence Warning)

None of the remedies worked (Changing the solver, increasing training iterations, feature engineering)

Discussion

Results

- Non-convergence -> logistic regression model does not have enough modeling power to fit the data
- The further out the prediction, the less accurate

Impact

- We showed that a model made of simple models can have similar performance Deep Learning (DL) models
- The Ordinal estimator can also be used with DL models.

Extensions

- With more computational power, train more sophisticated models (MLP, Gaussian Process, etc.) with more data
- Take advantage of the time series nature of the data. e.g. use a RNN model
- Use auxiliary data, such as weather forecasts, to enhance predictions

References

- [1] epistoteles (2021). Predicting Drought. <https://github.com/Epistoteles/predicting-drought>
- [2] Frank, E., & Hall, M. (2001). A simple approach to ordinal classification. In *European conference on machine learning* (pp. 145-156). Springer, Berlin, Heidelberg.
- [3] Minixhofer, Christoph (2021). Predict Droughts using Weather & Soil Data. From <https://www.kaggle.com/datasets/cdmnix/us-drought-meteorological-data>

Data

- 3100 prediction sites (US counties)

Each datapoint:

- 180 days of past meteorological indicators
- Weekly measured drought value (none to D4)
- Soil data for the prediction site

18 meteorological Indicators per day
32 soil features for each prediction site

Raw Data:

Train: 19 million rows

Validation: 2.2 million rows

Test: 2.2 million rows

After processing:

180 past days: 100k rows by 3810 features

14 past days: 1.4 million rows by 324 features

Example features of Raw data:

fips	date	PRECTOT	PS	QV2M	score
1001	2019-01-01	2.25	100.51	9.69	0.0

