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A Supervised Machine-Learning Approach to Stratigraphic Surface Picking in Well Logs From the Mannville Group of Alberta, Canada

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@JustinGosses

Predictatops

https://github.com/JustinGOSSES/predictatops

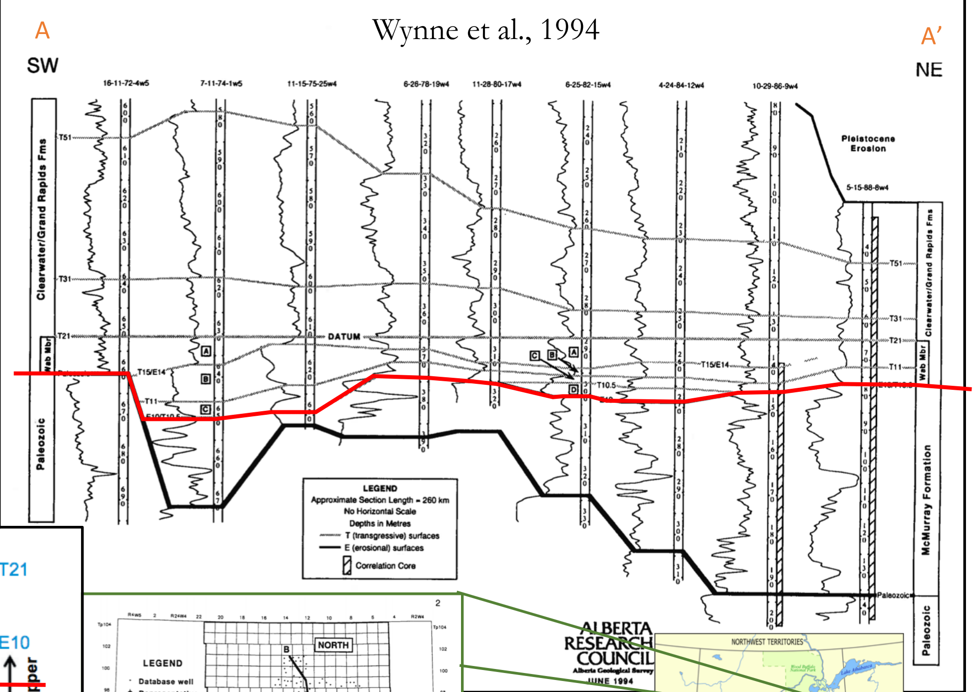
Talk Outline

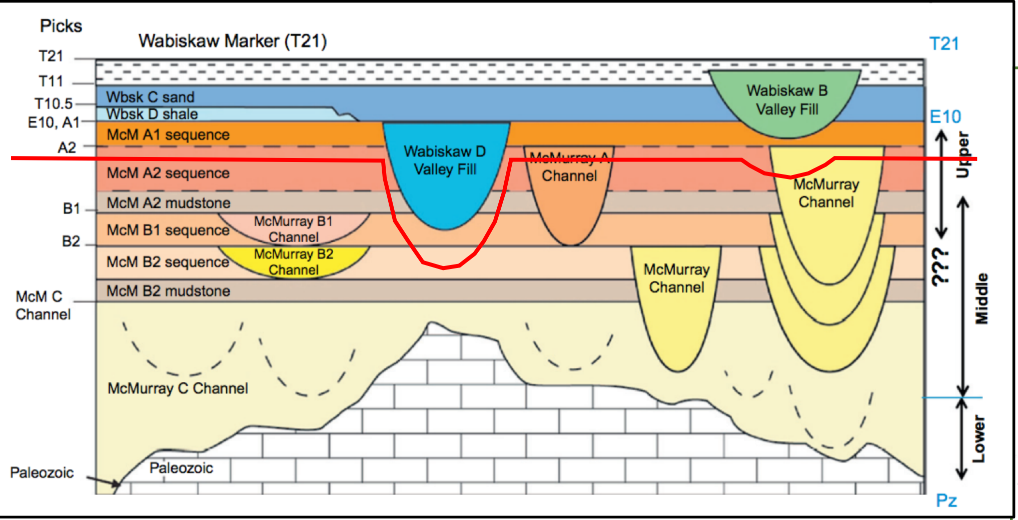
- Data: - Intro to an open-source dataset
- Theory - Human vs. machine-learning stratigraphy
- Methods - Introduction to Predictatops
- Application - How and when it might be useful

Predictatops https://github.com/JustinGOSSES/predictatops

Location: Mannville Group of Alberta, Canada
Goal: Predict Top McMurray
Dataset: 2193 wells, tops, & location data

Top McMurray is a regional transgressive, erosive surface. Dataset is public & described by Alberta Geological Survey Open File Report 1994-14





Hein et al., 2001

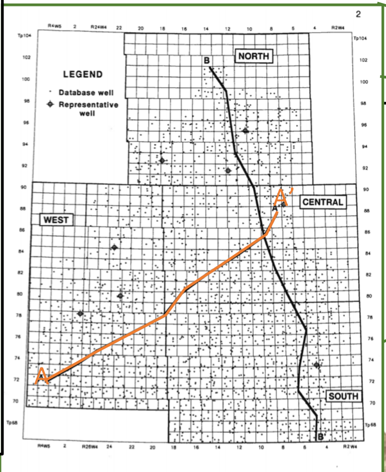
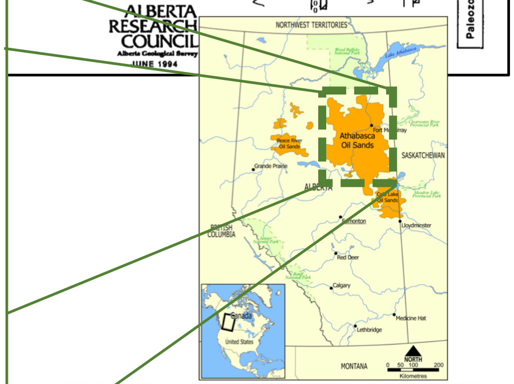


Figure 1. Study area with locations of wells, representative wells and cross sections.



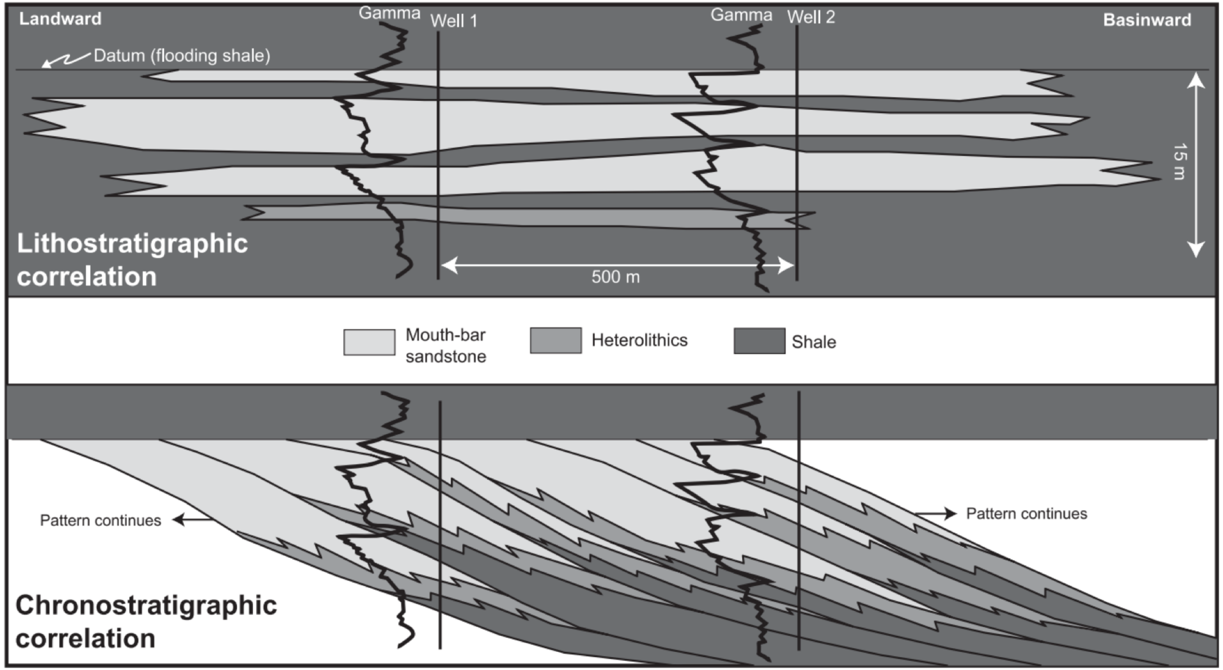
https://ags.aer.ca/document/OFR/OFR_1994_14.PDF

Different Types of Stratigraphic Labeling

Facies

Lithostratigraphy

Chronostratigraphy



Gani and Bhattacharya., 2005

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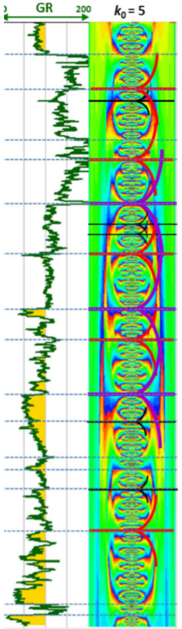
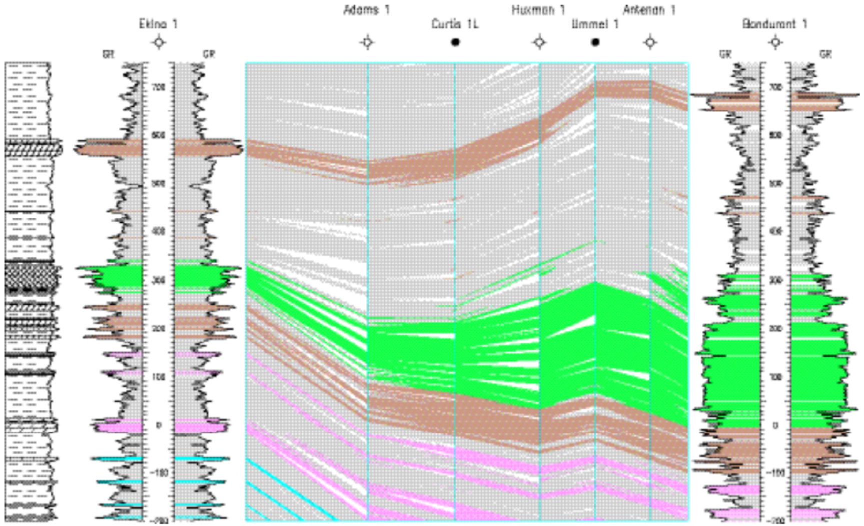
Machine-Learning in Stratigraphy

1D stacking pattern break identification via wavelet transforms



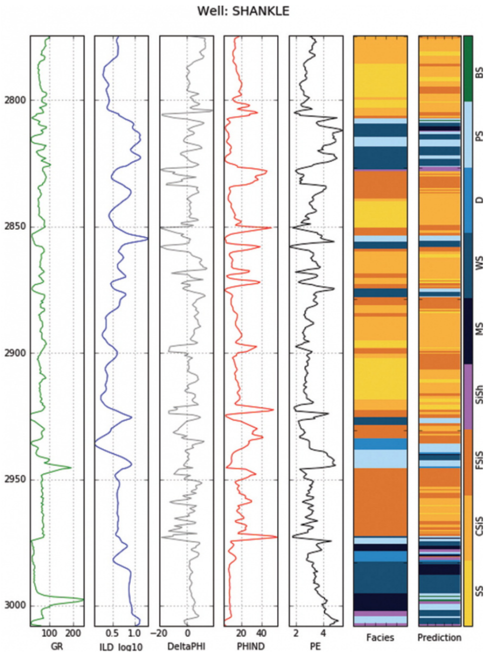
Ye et al., 2017

Correlator: Fortan program for well-to-well lithostratigraphy



Olea and Sampson, 2002, Kansas Geological Survey

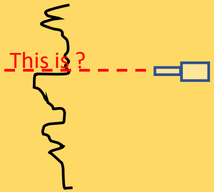
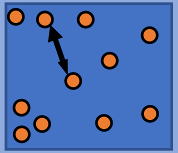
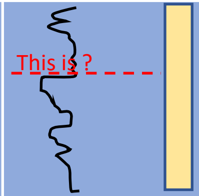
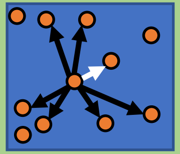
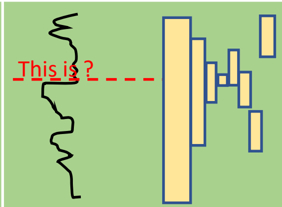
SEG facies prediction contest



Hall., 2016

https://wiki.seg.org/wiki/Facies_classification_using_machine_learning
Brendon Hall, Enthought
THE LEADING EDGE October 2016
https://github.com/seg/2016-ml-contest

Comparing Different Types of Stratigraphic Labeling to Find Key Parts

	Min # of wells	All training wells used in prediction	Wells compared to one another?	Information used from above or below a depth point?	What features & how are they used?	What is the prediction?
Facies	1	Probably	No		Classification	Facies labels for each depth point
Litho-stratigraphy	2	No			Curve matching: often dynamic time warping	Lines connecting 2 wells that may or may not overlay with tops
Chrono-stratigraphy	100s to 1000s (enough for models to be discovered)	Yes			Classification: Features similar to low-level human observations generated across different windows.	A Top Scored by distance between predicted & actual

Repackaging Chronostratigraphy as a Machine-learning Problem

Human Chrono-stratigraphy

Outcrop & analogue studies → Conceptual Chronostratigraphic Model + High-level human observations about wells relative to other wells & models → Geologist labeled Tops

↓

Supervised machine-learning Chrono-stratigraphy

Machine-learning model that can mimic human chronostratigraphic interpretation ← Machine-learning algorithm good at clustering, finding threshold, etc. to classify + Rule-based features programmatically created to mimic low-level human observations + Geologist labeled Tops in training wells

How to Code Low-Level Geologic Observations as Features?

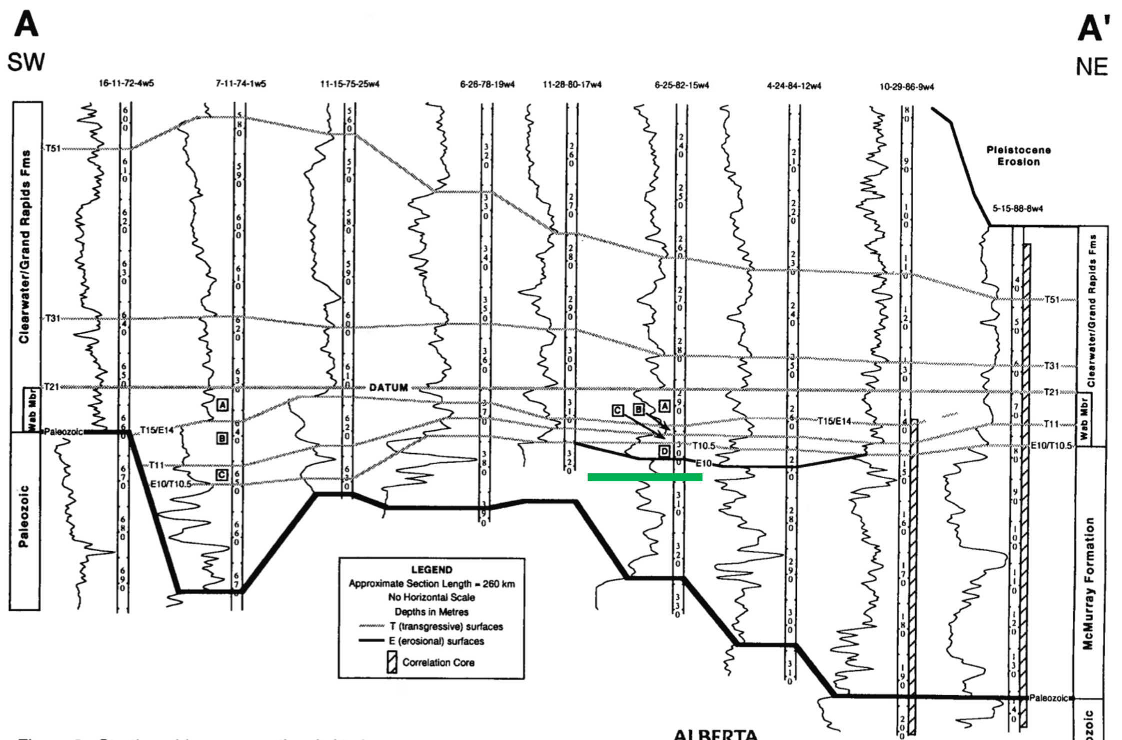


Figure 2. Stratigraphic cross section A-A' of Lower Cretaceous McMurray/Wabiskaw interval, Athabasca area, northeast Alberta.

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JUNE 1994

Hein et al., 2001

We want to create features to determine if each depth point is the top.

https://ags.aer.ca/document/OFR/OFR_1994_14.PDF

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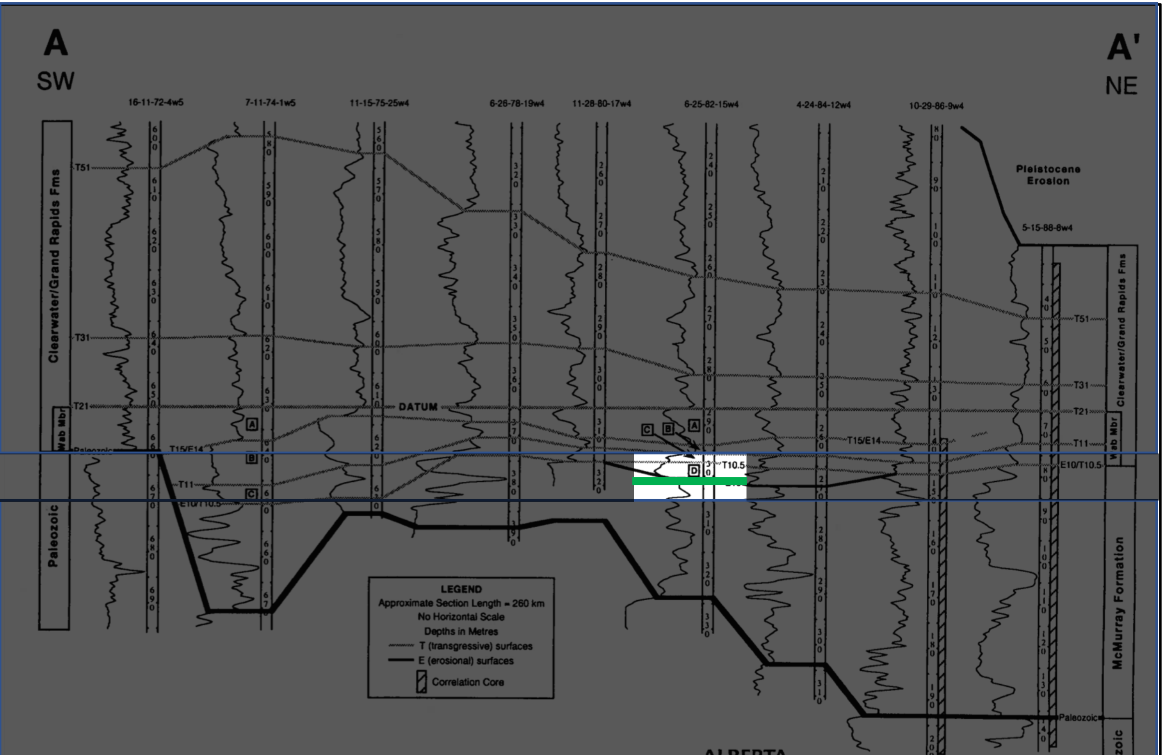

Figure 2. Stratigraphic cross section A-A' of Lower Cretaceous McMurray/Wabiskaw interval, Athabasca area, northeast Alberta.

A game: Pay attention to what you can't observe when aspects of the cross-section are taken away.

For each depth point, need to create features that gather information around it.

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How to Code Low-Level Geologic Observations as Features?

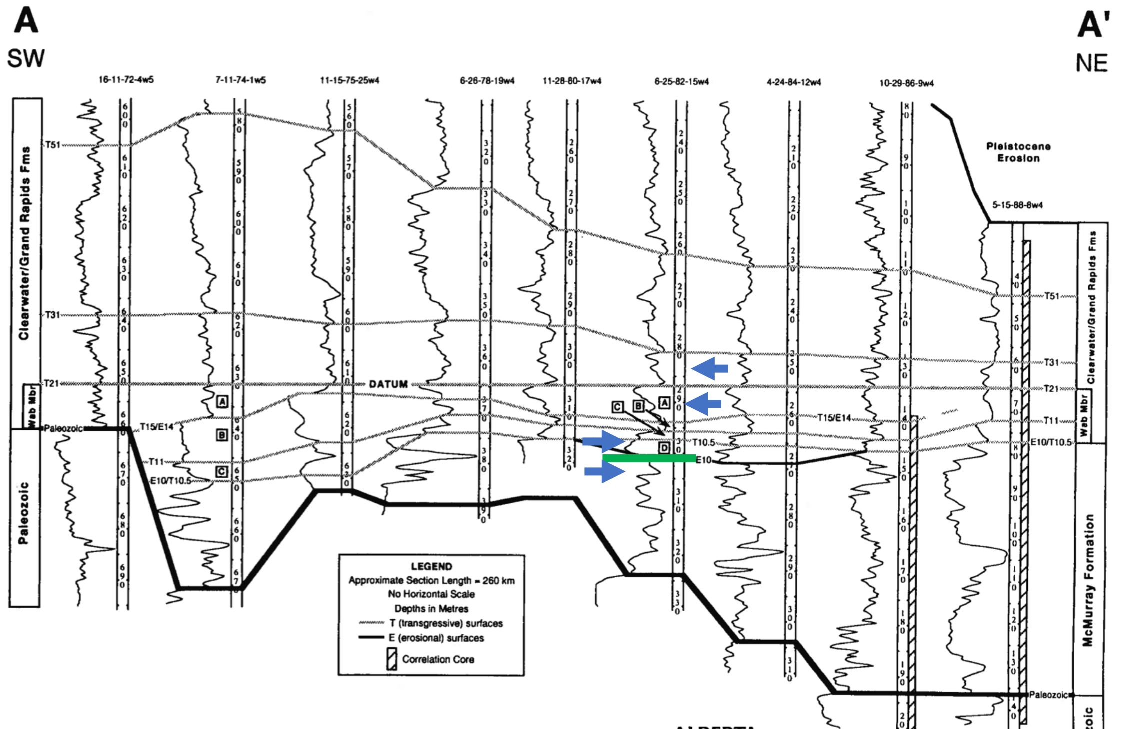

Figure 2. Stratigraphic cross section A-A' of Lower Cretaceous McMurray/Wabiskaw interval, Athabasca area, northeast Alberta.

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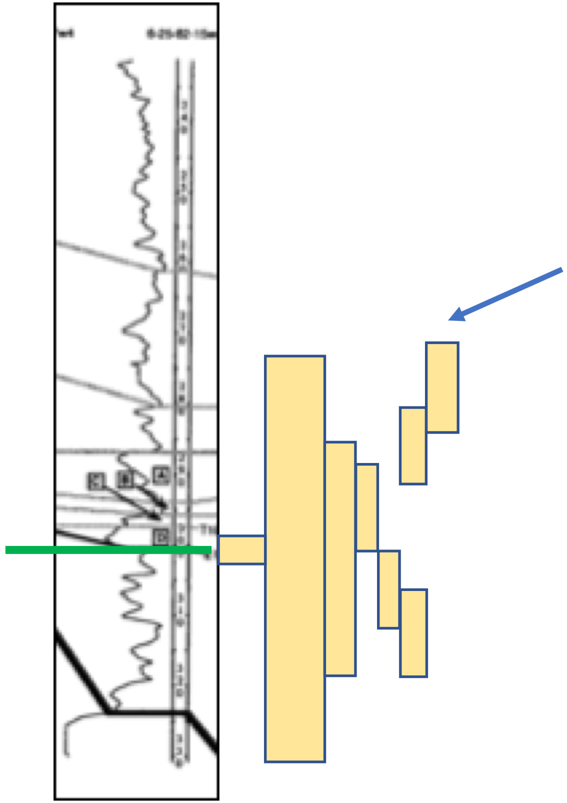
Neighboring training wells can be used for features: here unit thickness of neighbors represented by blue arrows.

How to Code Low-Level Geologic Observations as Features?



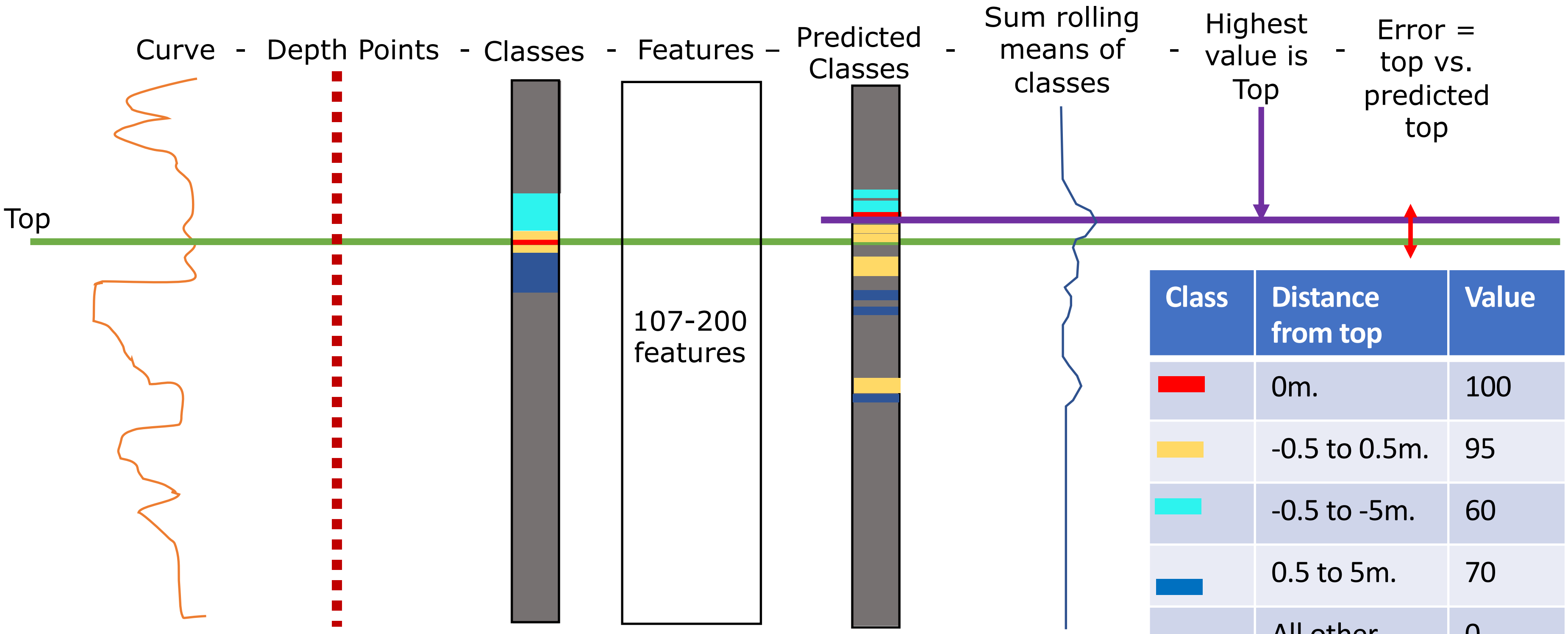
A single depth point with curve data

Within each window:

- Max, min
- Rate of change
- Variance
- Etc.

Information from above & below a point in question turned into features

Predicting a single top by creating classes based on distance from top



Class	Distance from top	Value
(red)	0m.	100
(yellow)	-0.5 to 0.5m.	95
(cyan)	-0.5 to -5m.	60
(blue)	0.5 to 5m.	70
(grey)	All other	0

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Predictatops

https://github.com/JustinGOSSES/predictatops

predictatops

0.1.0

Search docs

CONTENTS:

Docs » Usage   View page source

Usage

How to use predictatops in a project:

This uses Conda, so you might have to install that first.

In a terminal type the following commands -

Clone the predictatops repository first as we don't have have it PyPy yet:

```
git clone https://github.com/JustinGOSSES/predictatops.git
```

CD into the the folder:

```
cd predictatops
```

Create the conda environment with all the dependencies from the environment.yml at the top level folder:

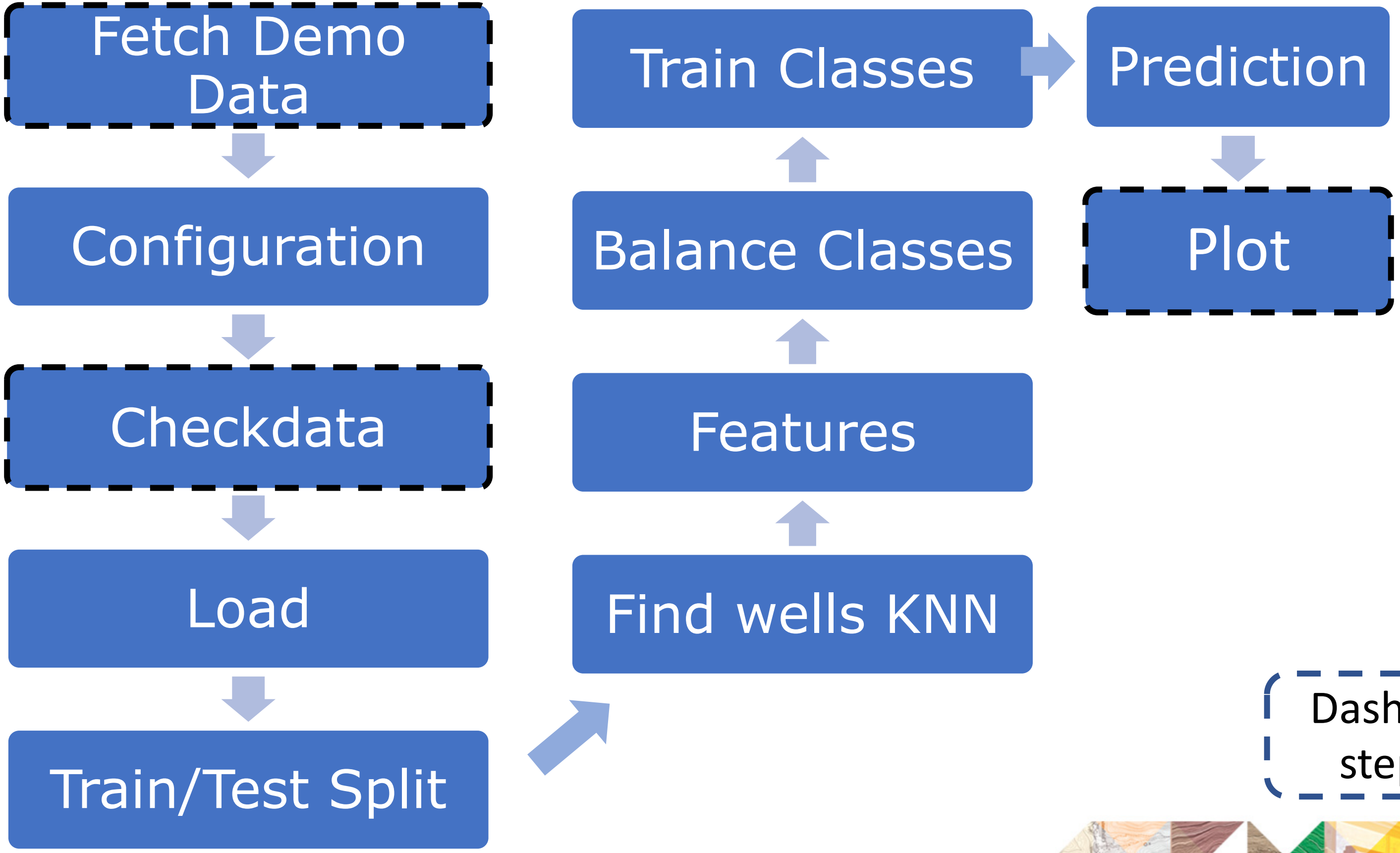
```
conda env create -f environment.yml
```

Activate that conda environment:

```
source activate predictatops
```

- Python code for top prediction
- M.I.T. License
- Run interactive in Jupyter or all at once via config file
- Alpha state

Predictatops ML pipeline



Dashed Black outline steps are optional

Parts of Machine-learning Code Worth Mention

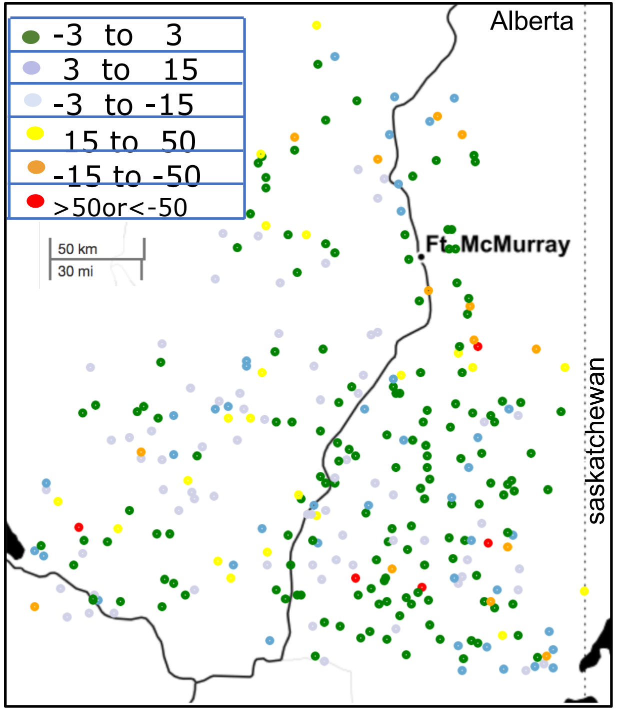
Create Train/Test **split before creating features**, so you don't cheat when you create features using spatial knowledge.

Class **rebalancing is critical** as the class you care most about (those nearest the top pick) will be the more sparsely populated in your original dataset.

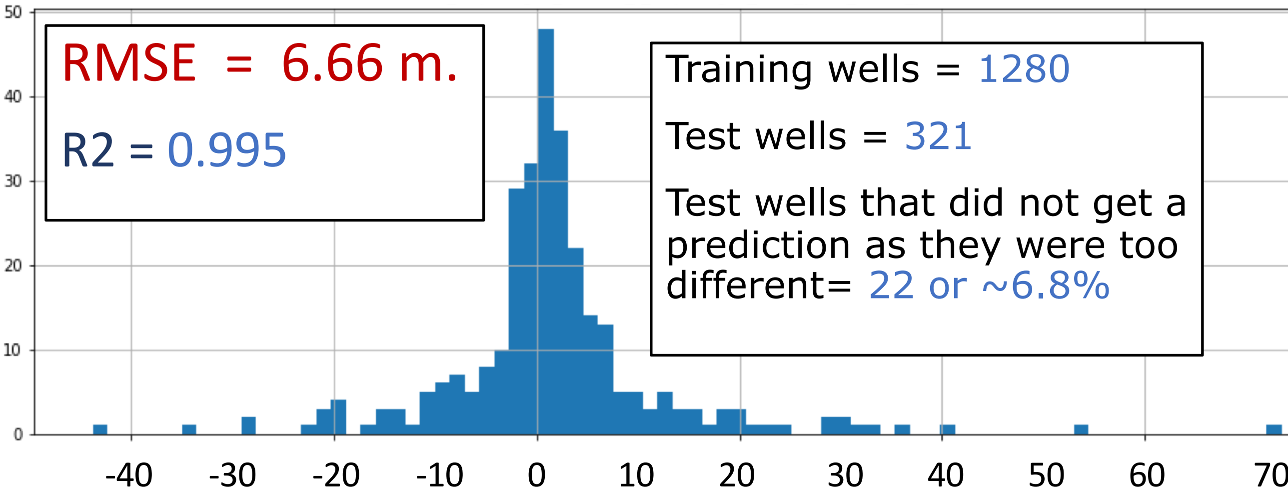
Sometimes a well doesn't have any depths predicted as remotely close to the top. Which is great! **Lets you know that well is different than training wells and needs a human touch**!

Results

Map test well prediction errors



Error [Predicted vs. Actual Top Depth meters]



Requirements for a well to be used:

Curves = ['ILD', 'NPHI', 'GR', 'DPHI']

Tops = Top McMurray, Base McMurray

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When to use? How to use?

Constraints on when to use?

- Need a large number of wells
- Need a large number of tops you trust
- Need tight enough well spacing to capture variance in order to produce model

Possible Applications

- **Time Reduction:** Interpret 1200 wells, and automate the other 1200
- **Compare Interpretations:** train two models in two areas, then predict on each other to see where differences in interpretation happen.
- **Better Represent Uncertainty:** easy to generate and track multiple top predictions & flag the wells with highest uncertainty

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- Coauthor: Licheng Zhang
- Additional Hackathon participants: Zhenshen Zong, Jonathon Parker
- Hackathon organizer Agile Geoscientific
- Open-Source Geoscience Libraries: Welly & Lasio!
- Dataset Suppliers!!!
  - Alberta Research Council & Alberta Energy Regulator.
  - Many authors of Alberta Geological Survey Open File Report 1994-14
    - Recently, AGS has made public 35,000 more tops, but the logs need to purchased.

Conclusions

Philosophy:

- Instead of trying to encode a geologic model in code directly or find mathematical patterns in the raw data, create features that map to low-level geologic observations & then let the program figure out the relationships that human would describe with a model.

Requirements for use: 1000s of wells & acceptable to have slightly worse than human performance

Possible Application: Time reduction on regional scale work & new uncertainty management options

Future Work: Different algorithms + More features + Different Datasets + Better Visualizations + Better Docs

Predictatops https://github.com/JustinGOSSES/predictatops

References

- Gani and Bhattacharya (2005) Lithostratigraphy Versus Chronostratigraphy In Facies Correlations of Quaternary Deltas: Application of Bedding Correlation, River Deltas—Concepts, Models, and Examples SEPM Special Publication No. 83, SEPM (Society for Sedimentary Geology), ISBN 1-56576-113-8, p. 31–48
- Gosses, J.C., 2019, JustinGOSSES/predictatops: v0.0.3: Zenodo, doi:10.5281/zenodo.3247092.
- Hein (2013) A Regional Geologic Framework for the Athabasca Oil Sands, Northeastern Alberta, Canada,Heavy-oil and Oil-sand Petroleum Systems in Alberta and Beyond: AAPG Studies in Geology 64, Chapter: 7, American Association of Petroelum Geologists.
- Hall, B. (2016) Facies classification using machine learning, The Leading Edge, 35 (10): 906-909.
- Hein, F. J., and Dolby, G., 2001, Regional lithostratigraphy, biostratigraphy and facies models, Athabasca oil sands deposit, northeast Alberta: Ann. Conv. Proc. Rock the Foundation (Calgary), Can. Soc. Petroleum Geologists, 3 p.
- Olea and Sampson (2003) User's Manual For Correlator, Version 5.2, Lawrence, Kansas; Kansas Geological Survey Mathematical Geology Section
- Wynne et al., (1994) Athabasca Oil Sands Database McMurray/Wabiskaw Deposit, Open-File-Report 1994-14, Alberta, Canada; Alberta Geological Survey. Links to report & dataset.
- Ye et al. (2017) Rapid and Consistent Identification of Stratigraphic Boundaries and Stacking Patterns in Well Logs – An Automated Process Utilizing Wavelet Transforms and Beta Distributions, SPE Annual Technical Conference and Exhibition, DOI: 10.2118/187264-MS