Machine Learning Visualization for Big Data Analysis

Cmpt 733 – Big Data Programming 2

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Analysis of Big Data via ML - Outline

- Machine learning tasks
- Vis for ML
- ML for Vis
- Google Compute
- Best of: Weather model vis

Tasks performed **by** and **for** ML

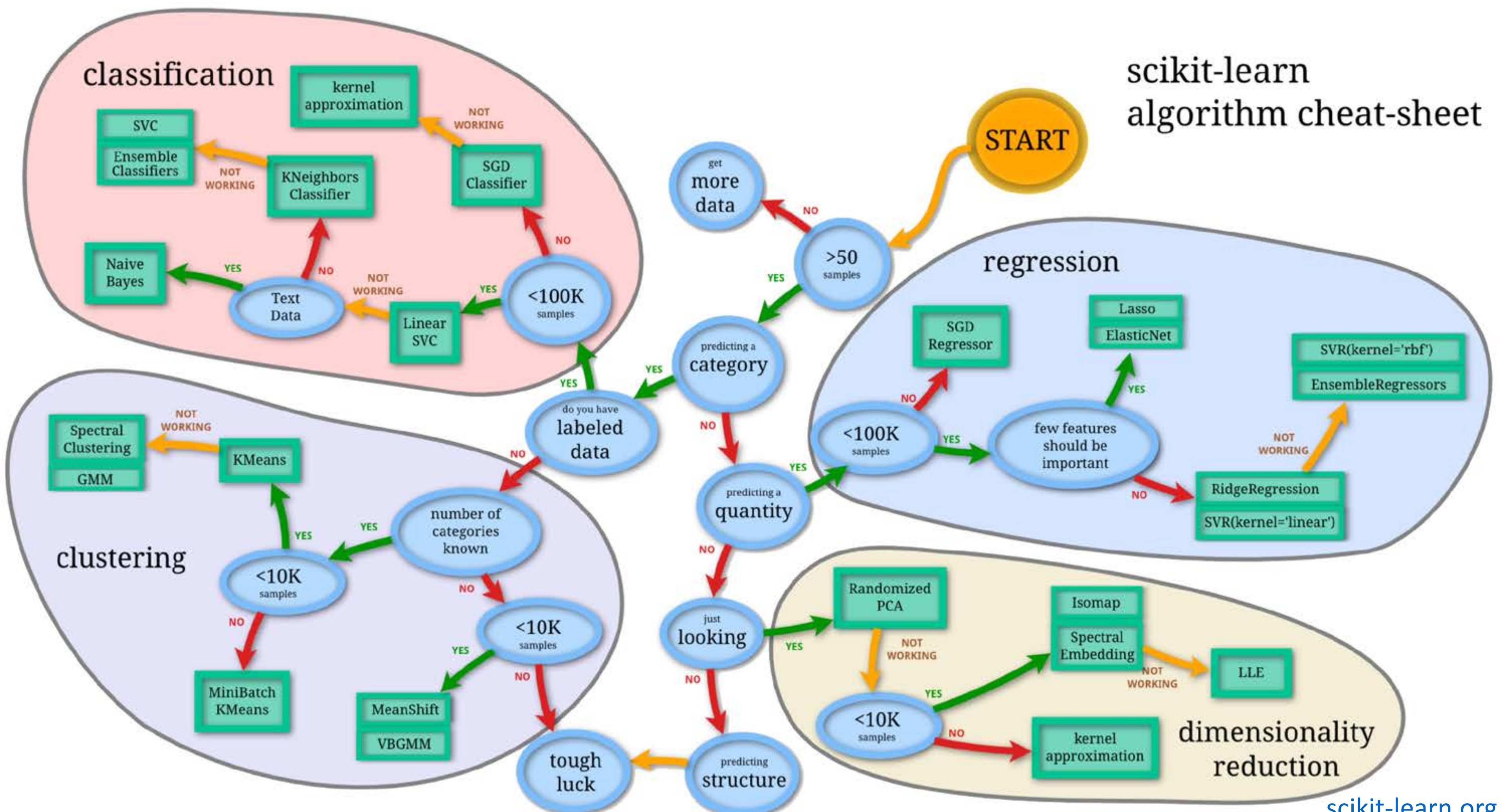
ML Task Categories: By Output

- Classification
- Regression
- Clustering
- Association rules
- Forecasting
- Dimensional reduction
- Density estimation

[wikipedia]

ML Task categories: By Training

- **Supervised learning**
  - Inputs and desired outputs are given
  - Find rule that maps unseen inputs to outputs
- **Semi-supervised learning**
  - Supervised learning with only few of the target outputs given
- **Active learning**
  - Data is not given, but asked for
- **Unsupervised learning**
  - No labels given
  - Discover hidden patterns and structure in inputs
  - Feature learning
- **Reinforcement learning**
  - Rewards/punishments given as feedback to actions in dynamic environment



scikit-learn.org

Tasks **for** Machine Learning

For a given problem

- Choose a model class & estimator, loss function, optimization method
- Determine the right training data (attributes, distribution)

For a given model class

- Estimate model parameters to fit with given observations
- Make predictions, determine and communicate uncertainty
- Analyse model behaviour over a region of inputs
- Understand how model works, explain its decision making
- Validate fit of training assumptions vs operating conditions

All of the above: data-driven

Some: human-in-the-loop

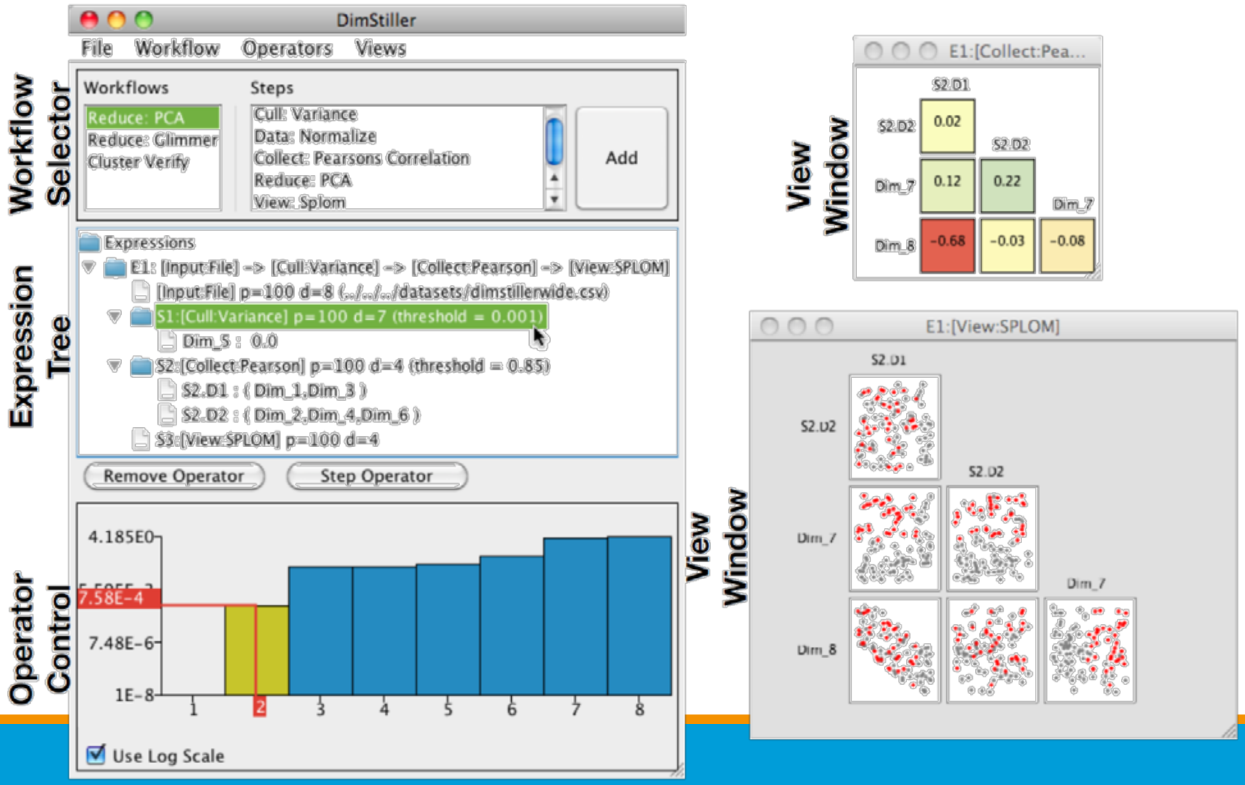
Cluster Analysis

Cluster Visualization

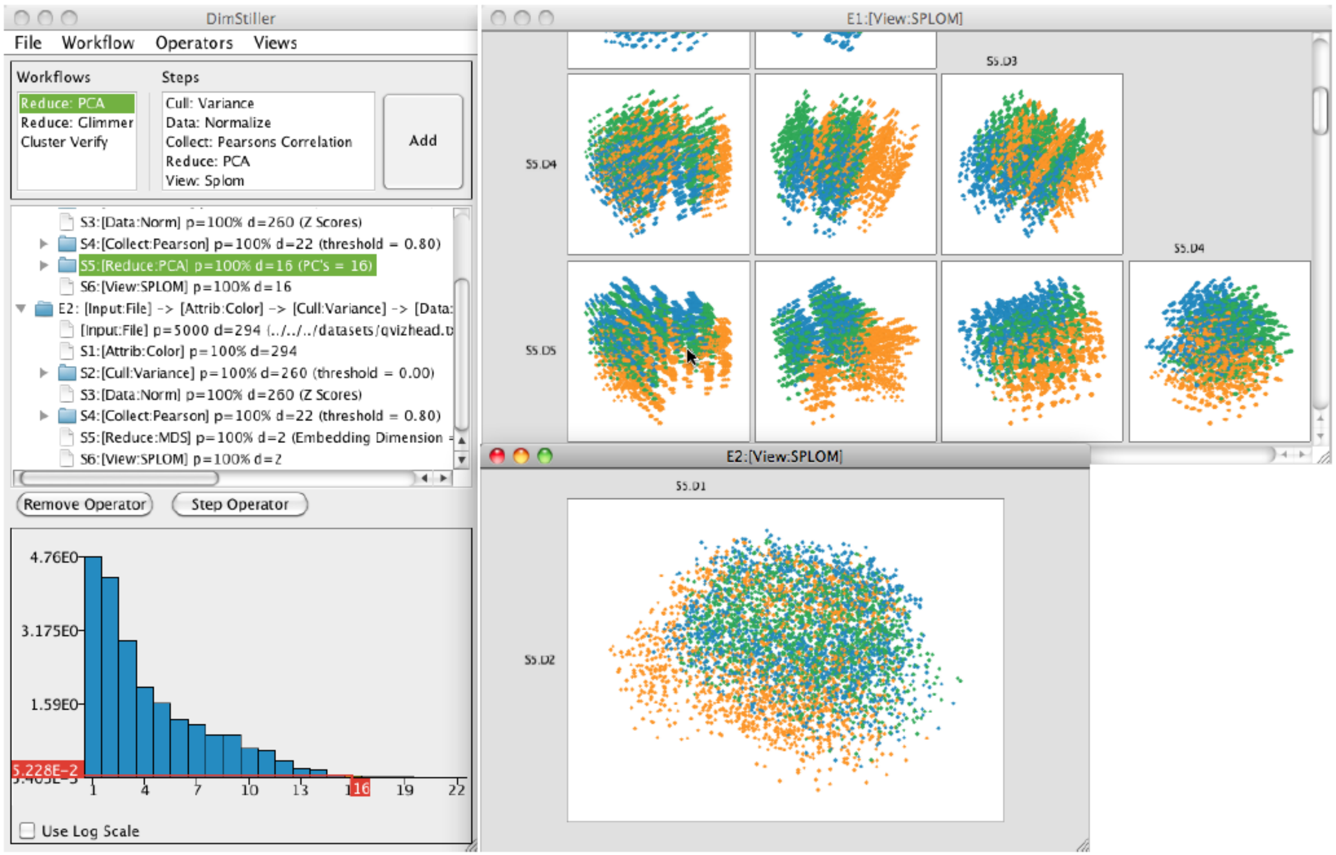
- Treat cluster label as categorical variable
- Multi-variate vis technique with encoding for label attribute

Example: DimStiller Workflows

- Goal: Understand and transform input data
- Chain operators together into pipelines



DimStiller Cluster Analysis Example



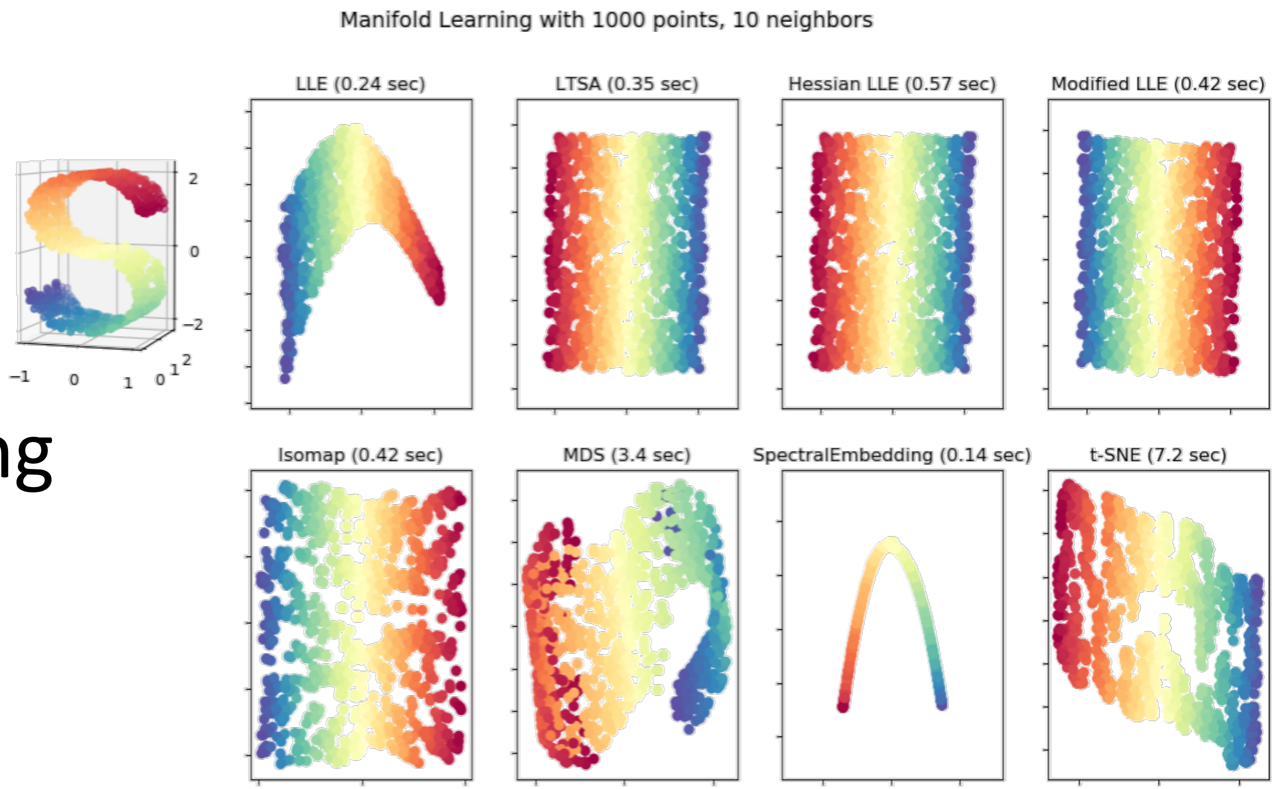
Dimension Reduction

Dimension Reduction

- PCA
- ICA

Manifold Learning

- t-SNE
- LLE
- …



[scikit-learn.org]

Model Explanation

ML model explainability

What features have the biggest impact?

- Debugging
- Informing feature engineering
- Directing future data collection
- Informing human decision-making
- Building Trust

https://www.kaggle.com/learn/machine-learning-explainability

Explain: Permutation importance

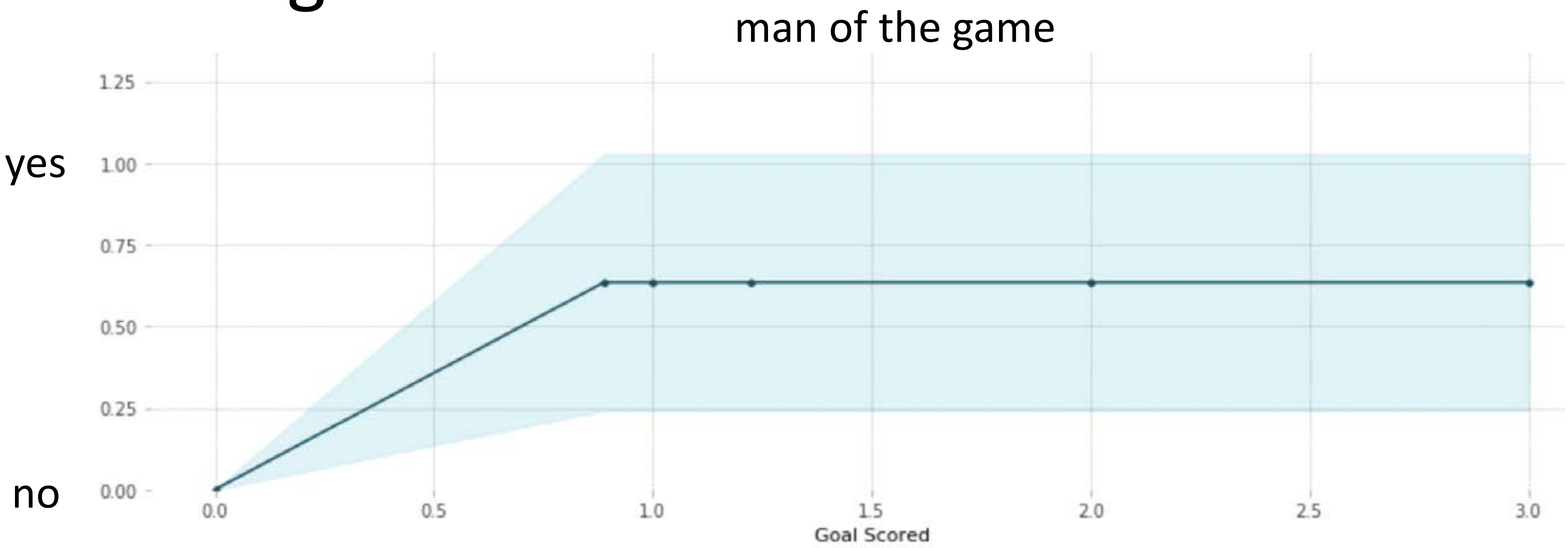
- For a trained model, per column of the data:
  - Randomly shuffle column values
  - Performance deterioration as feature importance

Height at age 20 (cm)	Height at age 10 (cm)	...	Socks owned at age 10
182	155	...	20
175	147	...	10
...	...	...	...
156	142	...	8
153	130	...	24

https://www.kaggle.com/dansbecker/permutation-importance

Explain: Partial dependence plots

- Use trained model
- Show prediction as feature in one row is varied
- Average over all rows

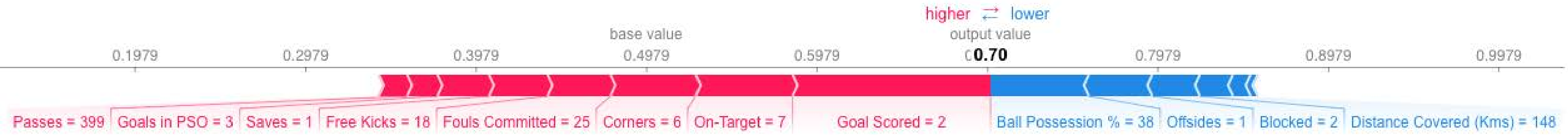


https://www.kaggle.com/dansbecker/partial-plots

Explain: SHAP values

- How much does a particular prediction change, if a feature is reset to a base value?
- Additive: *SUM of (SHAP values for all features) = prediction - prediction_for_baseline_values*

- "Man of the match" example:



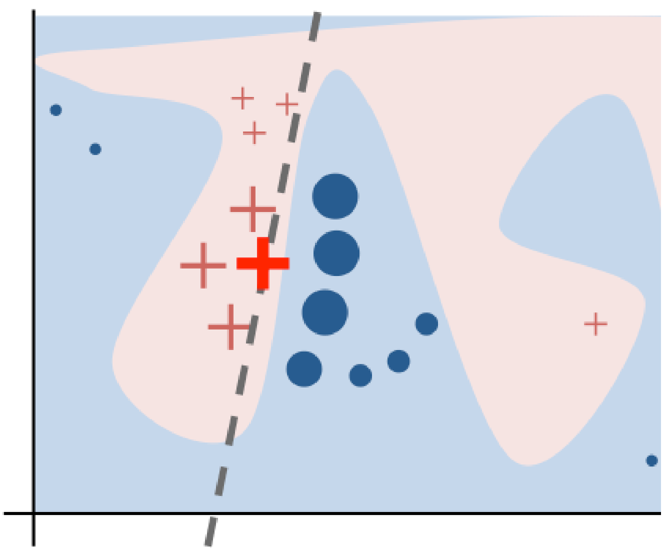
SHAP calculation

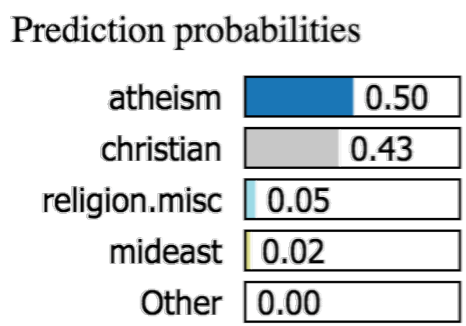
$$\phi_i(f,x) = \sum_{z' \subseteq x'} \frac{|z'|!(M-|z'|-1)!}{M!}\left[f_x(z') - f_x(z' \setminus i)\right]$$

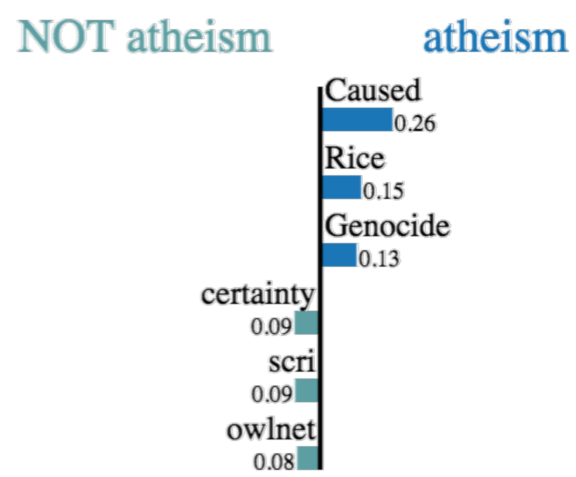
- *z'* represents feature vectors, where some feature values are 'missing' (are at base level)
- *i* indicates the feature of interest
- Normalization balances number of combinations
- Computed via local linear approximation (LIME)

Model explanation via local linear approximation (LIME)

- [Lime: Explaining the predictions of any ML classifier]
- SHAP values are a generalization of this







Deep Learning / Neural Networks

Visual Analytics in Deep Learning: An Interrogative Survey for the Next Frontiers

Fred Hohman, *Member, IEEE,* Minsuk Kahng, *Member, IEEE,* Robert Pienta, *Member, IEEE,*
and Duen Horng Chau, *Member, IEEE*

Abstract—Deep learning has recently seen rapid development and received significant attention due to its state-of-the-art performance on previously-thought hard problems. However, because of the internal complexity and nonlinear structure of deep neural networks, the **underlying decision making processes for why these models are achieving such performance are challenging** and […]

- [TVCG 2018] Web version

Interrogative Questions

WHY
- Interpretability & Explainability
- Debugging & Improving Models
- Comparing & Selecting Models
- Teaching Deep Learning Concepts

WHO
- Model Developers & Builders
- Model Users
- Non-experts

WHAT
- Computational Graph & Network Architecture
- Learned Model Parameters
- Individual Computational Units
- Neurons in High-dimensional Space
- Aggregated Information

HOW
- Node-link Diagrams for Network Architecture
- Dimensionality Reduction & Scatter Plots
- Line Charts for Temporal Metrics
- Instance-based Analysis & Exploration
- Interactive Experimentation
- Algorithms for Attribution & Feature Visualization

WHEN
- During Training
- After Training

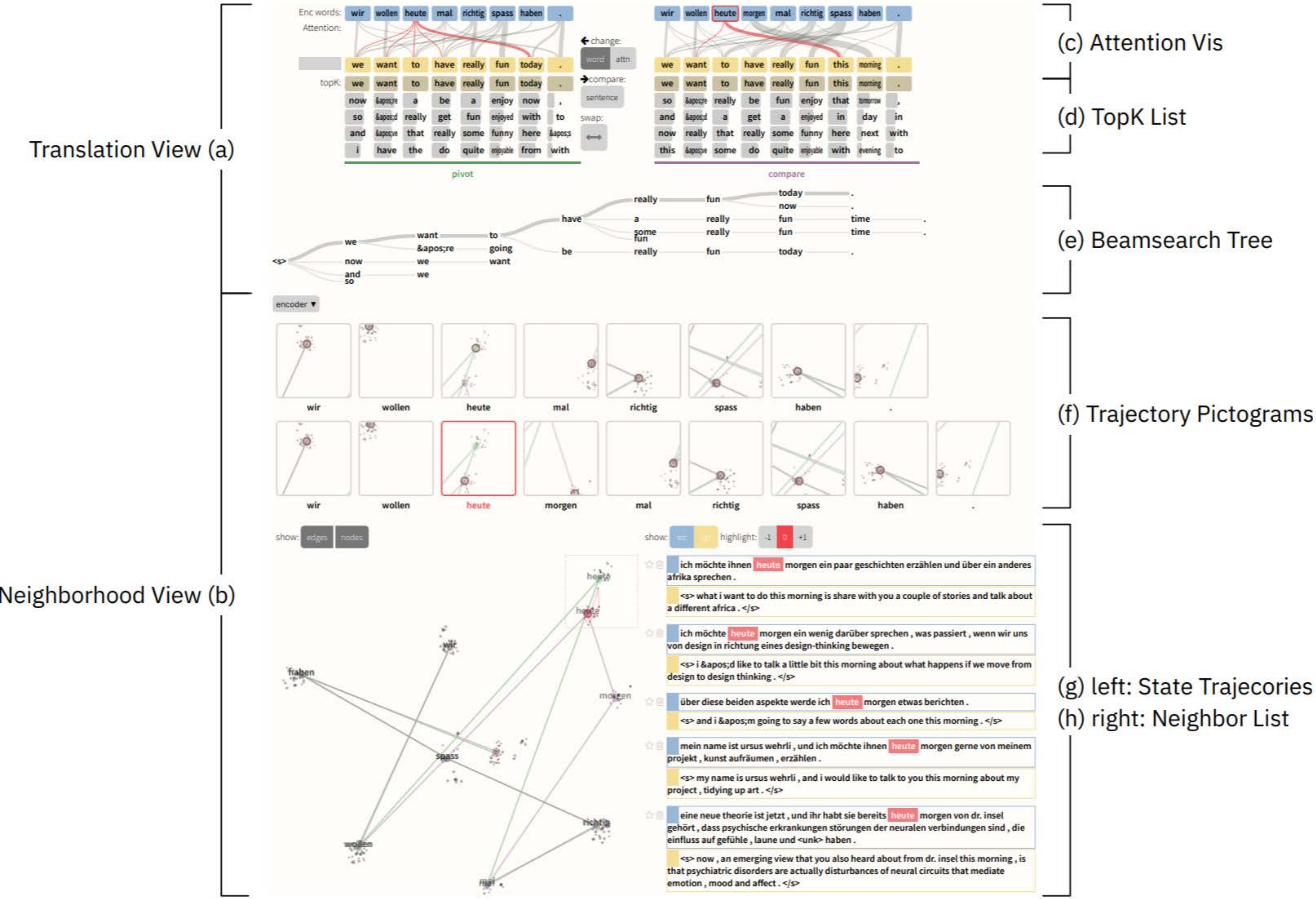
WHERE
- Publication Venue

[Web version]

Sequence model visualization

- Examine model decisions
- Connect decisions to previous examples
- Test alternative decisions

- See [Video] at https://seq2seq-vis.io/



Translation View (a)
Neighborhood View (b)
(c) Attention Vis
(d) TopK List
(e) Beamsearch Tree
(f) Trajectory Pictograms
(g) left: State Trajecories
(h) right: Neighbor List
Enc words:
Attention:
topK:
change:
compare:
swap:
pivot
compare
encoder
show:
highlight:

Further directions

Debugging tools

- Tensorboard: Visualizing Learning
- Visdom (only supports (Py)Torch and numpy)

Explainables

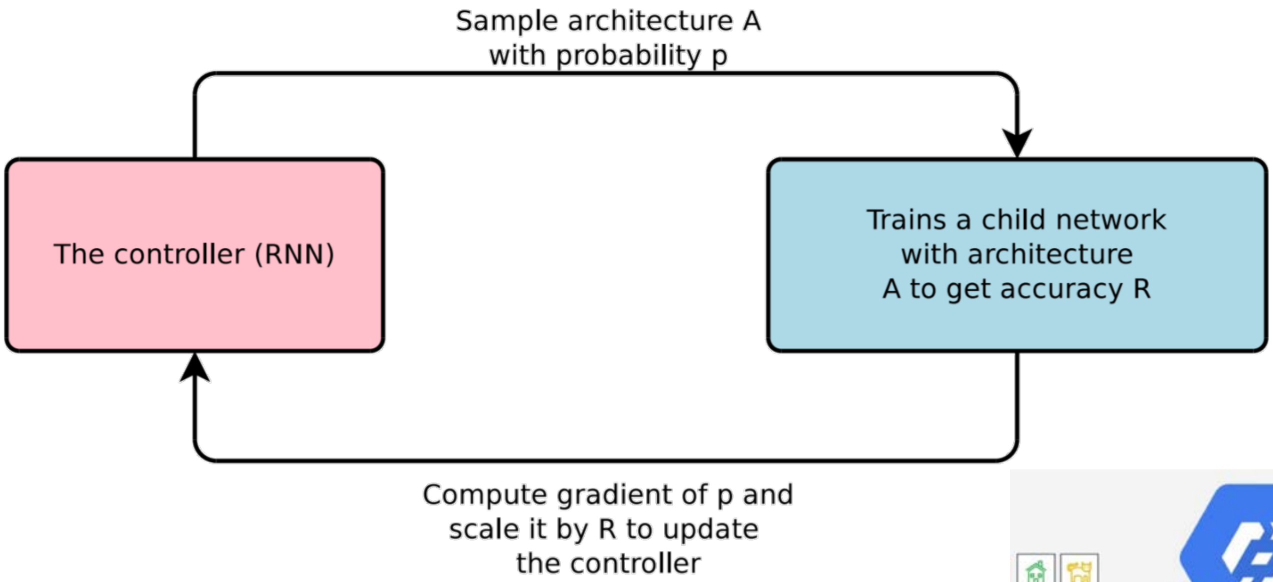
- R2D3 ← DEMO
- Tensorboard Playground

Model visualization

- Seq2Seq Vis: http://lstm.seas.harvard.edu/client/index.html
- Building blocks of interpretability

Google Compute

AutoML - Neural Architecture Search



- Given a dataset, produce Model
- Serve model output via REST API

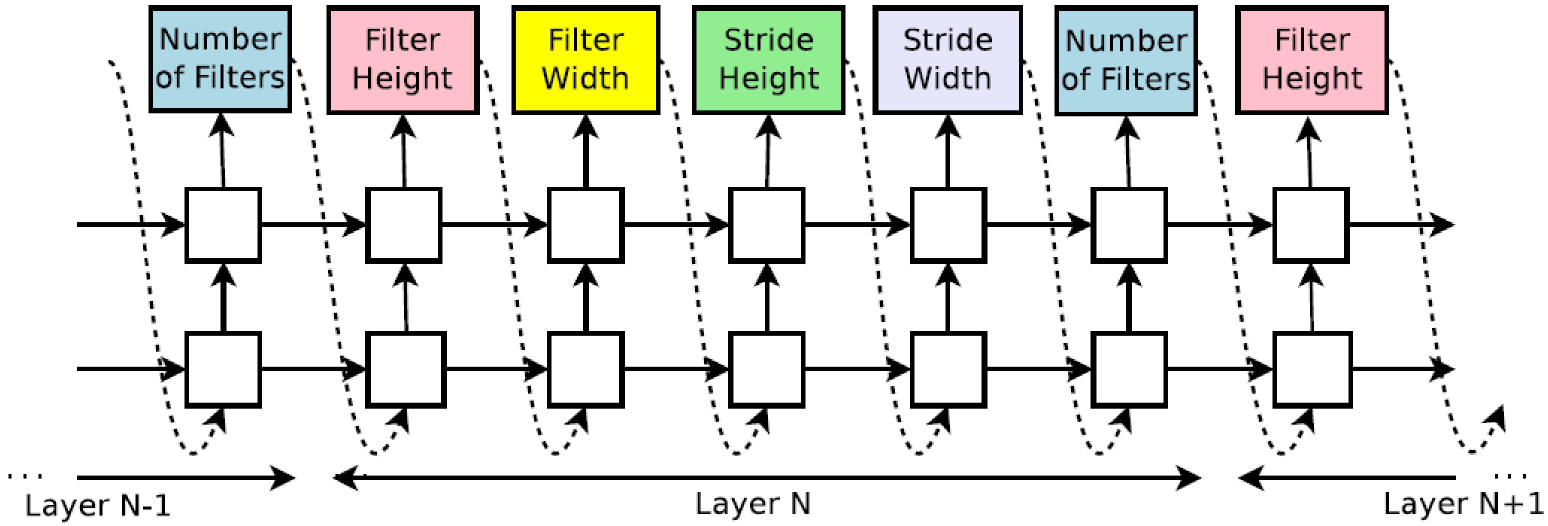
How:

- Controller suggests architecture for better R
- Combined with evolution

[Interview with Quoc Le, Google] [Zoph, Le ICLR 2017]

AutoML

- Controller is implemented as RNN
- Generates string to define architecture
- Speed-up: Transfer learning for architecture and weights



[Interview with Quoc Le] [Zoph, Le ICLR 2017]

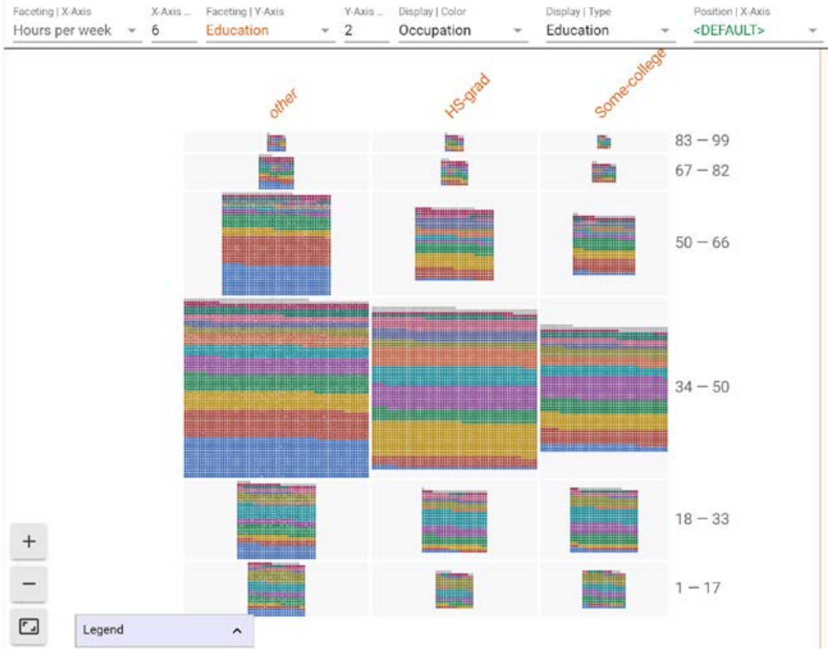
Google Compute Platform

- Big Query: Cloud data warehouse with ML
  - Beware of the pricing

- Vis via Data Studio (free)
  - https://cloud.google.com/bigquery/docs/visualize-data-studio

Google Facets

- https://pair-code.github.io/facets/

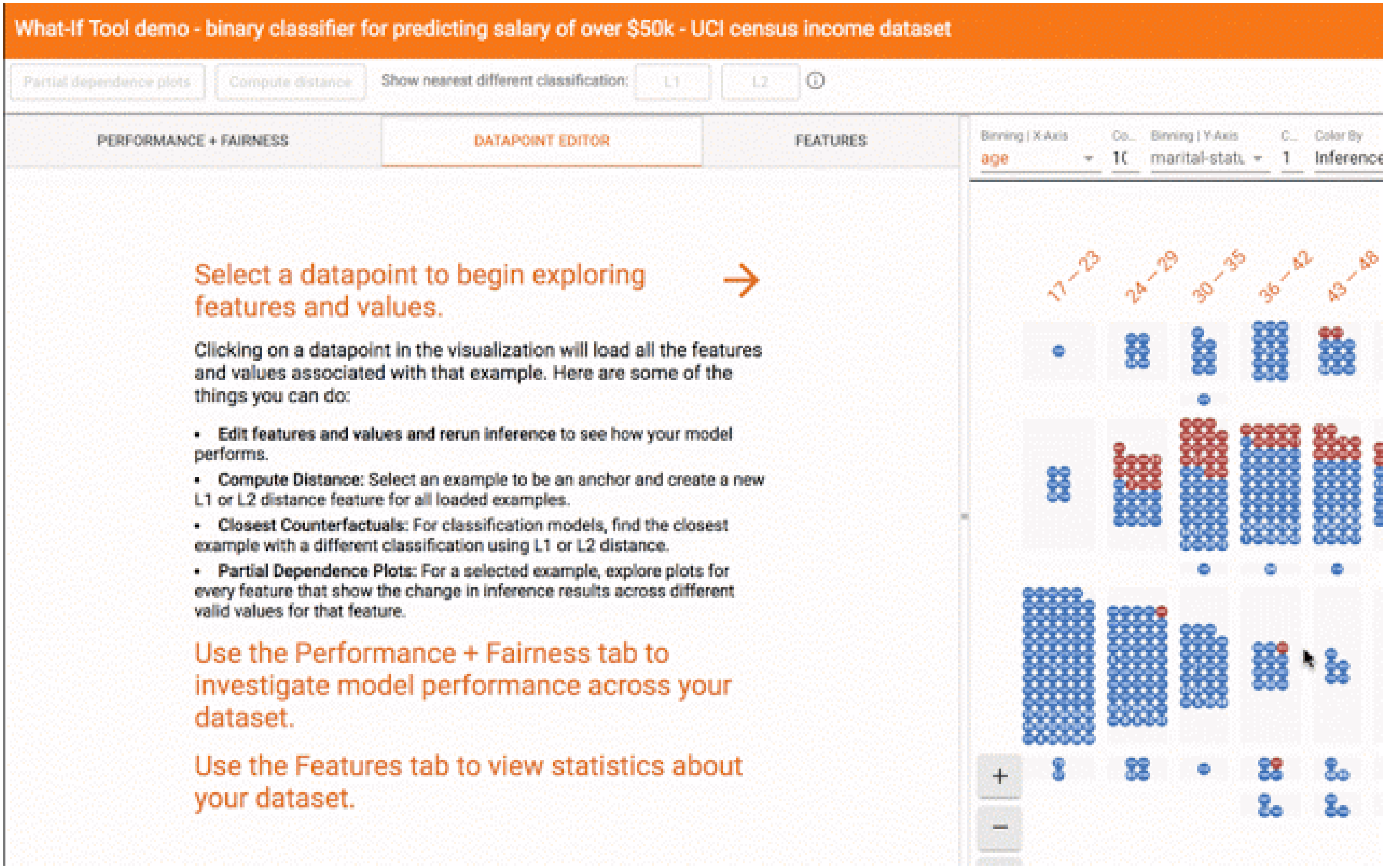


Uncover issues:

- Unexpected feature values
- Missing feature values for a large number of examples
- Training/serving skew
- Training/test/validation set skew

- Evolved into What-If-Tool

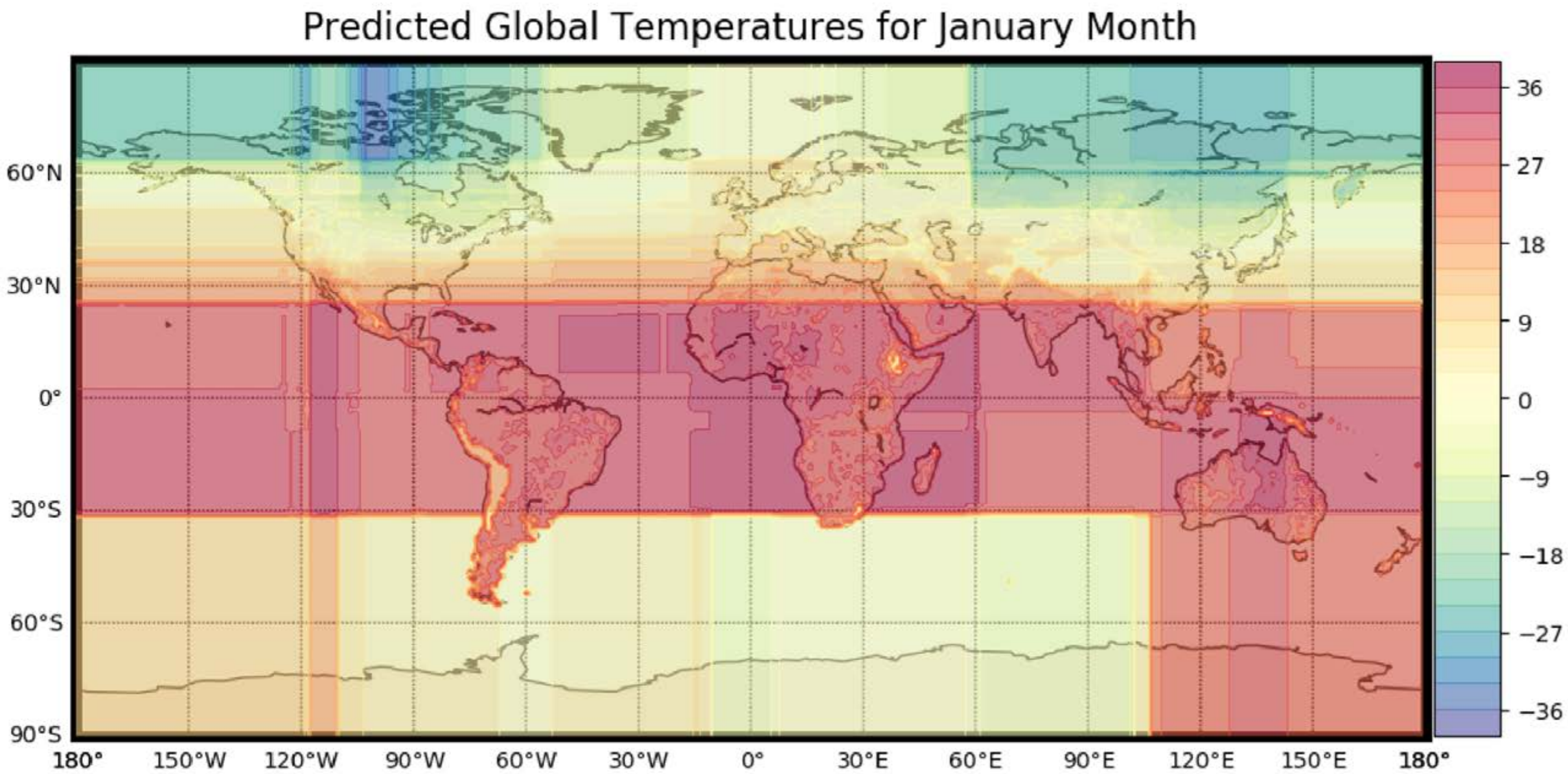
What-If-Tool (Google PAIR)



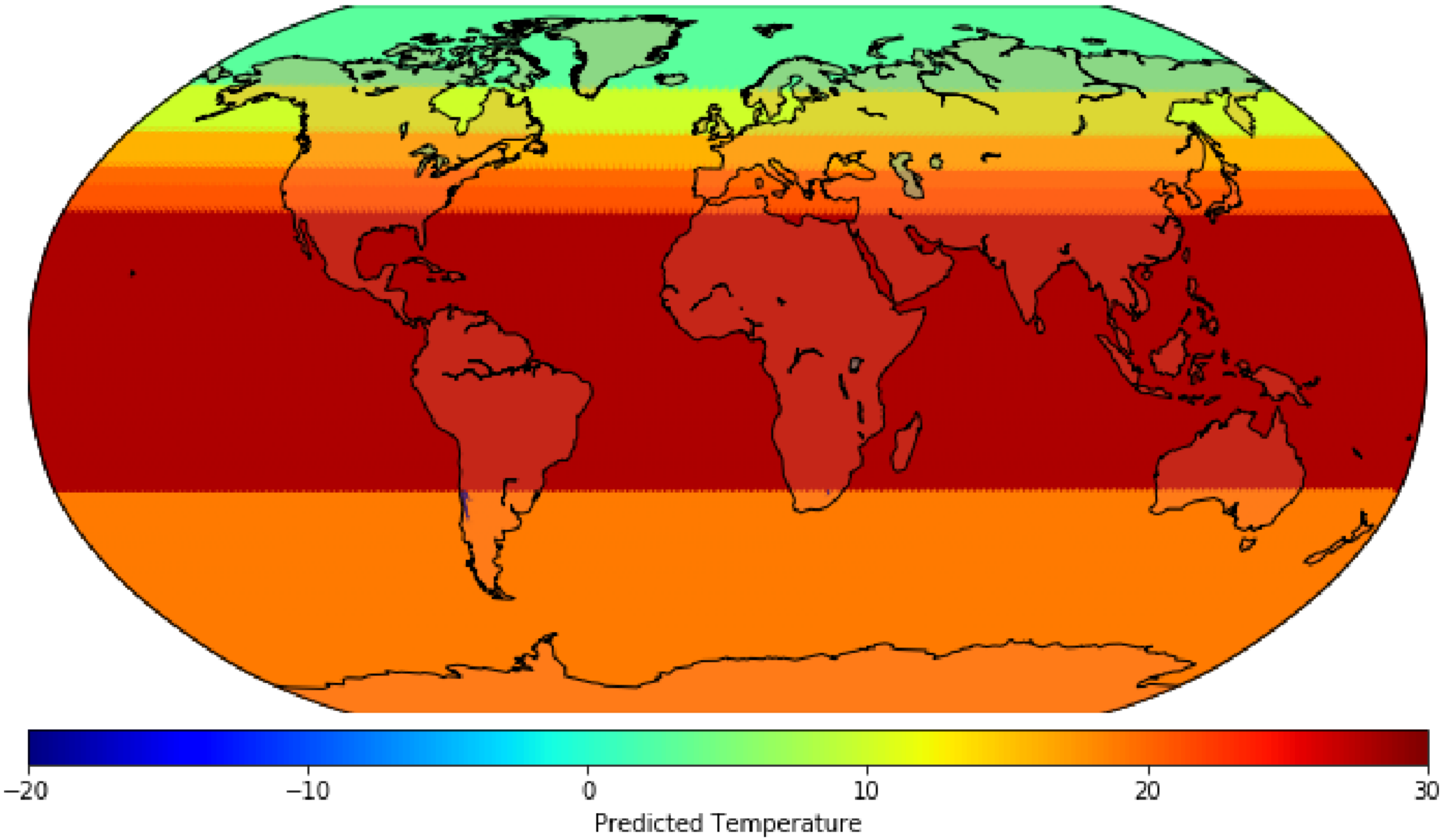
Weather Model Visualizations

Selected solutions from Assignment 3 – Task 2 B1

Anurag Bejju – GBT Model

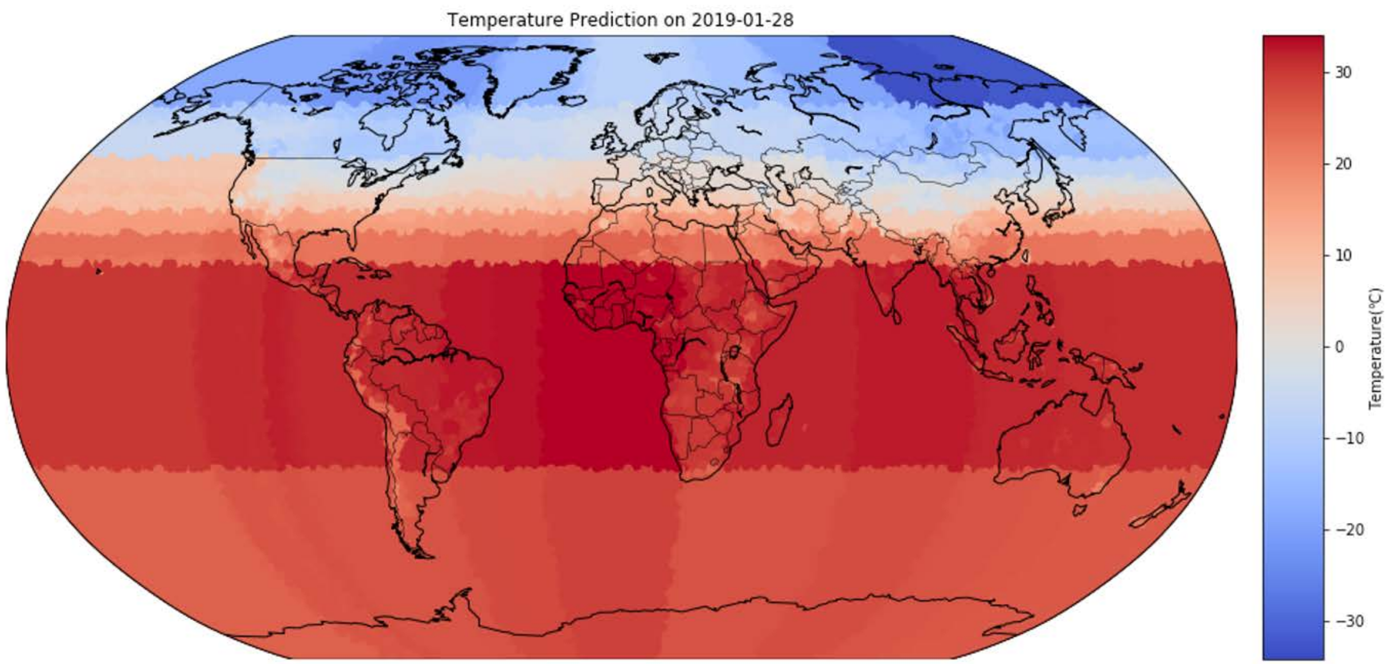


Aisuluu Alymbekova



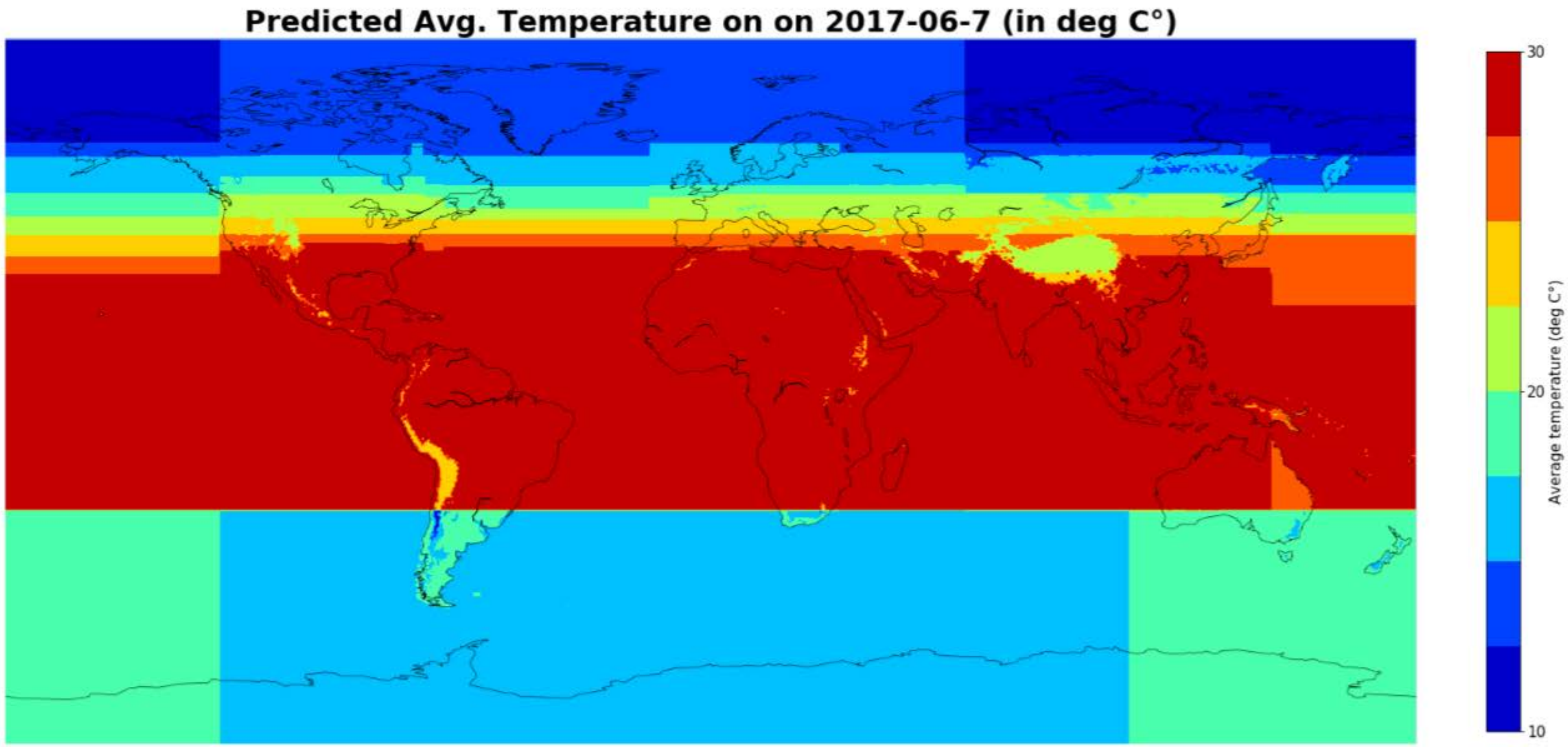
Andong (Anton) Ma

Fg3 is the dense heat-map generated by my model. Which we can easily evaluate as not good, because it shows that the temperature of southern earth is all above 0 C°, even in the South Pole.

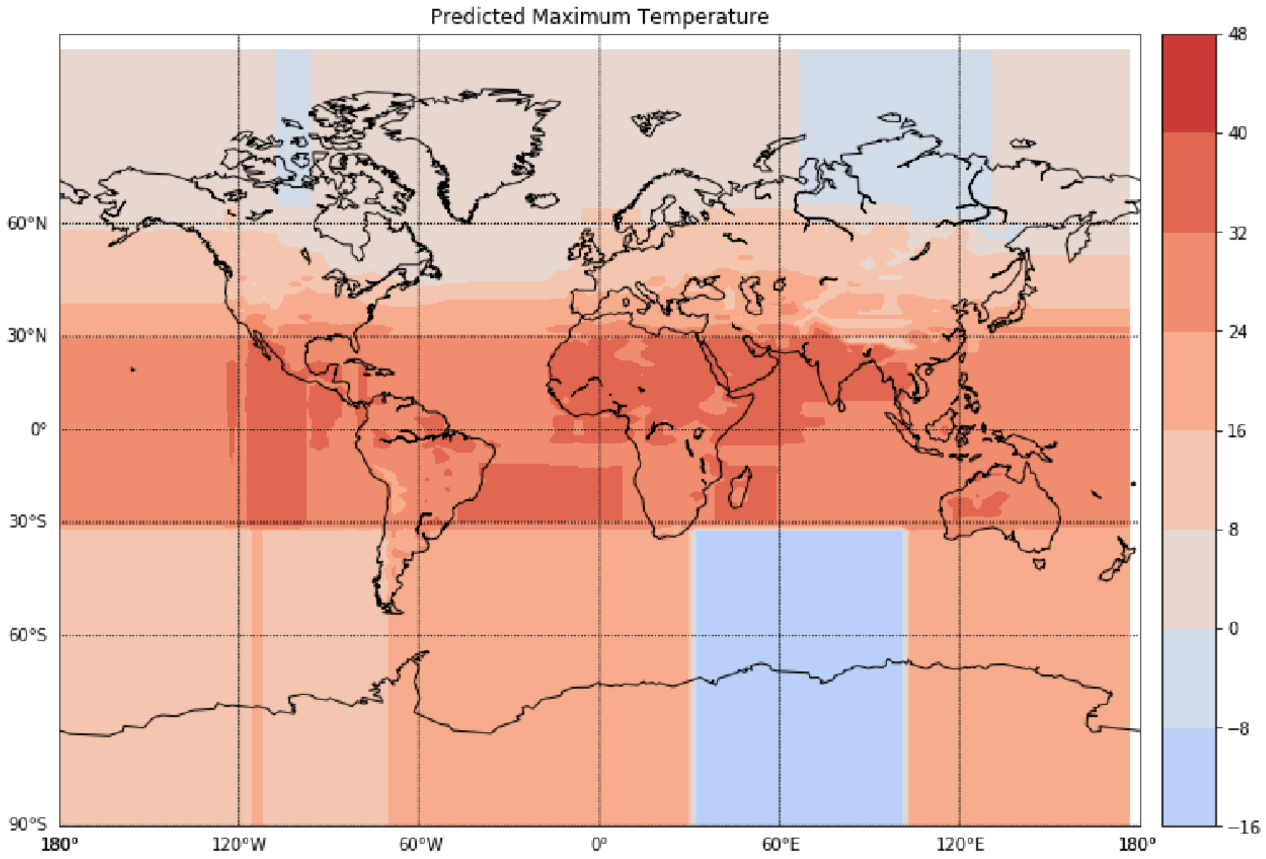


Fg 3

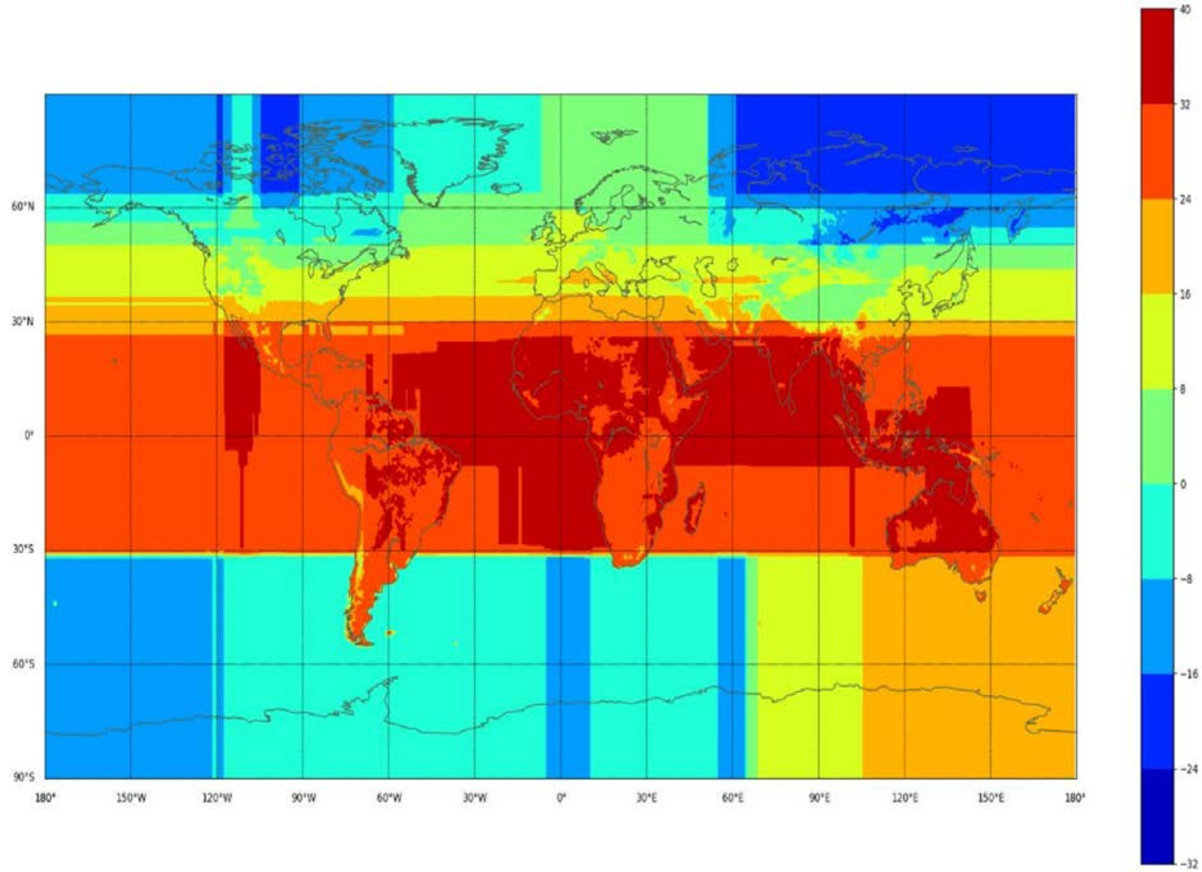
Abhishek Sunnak



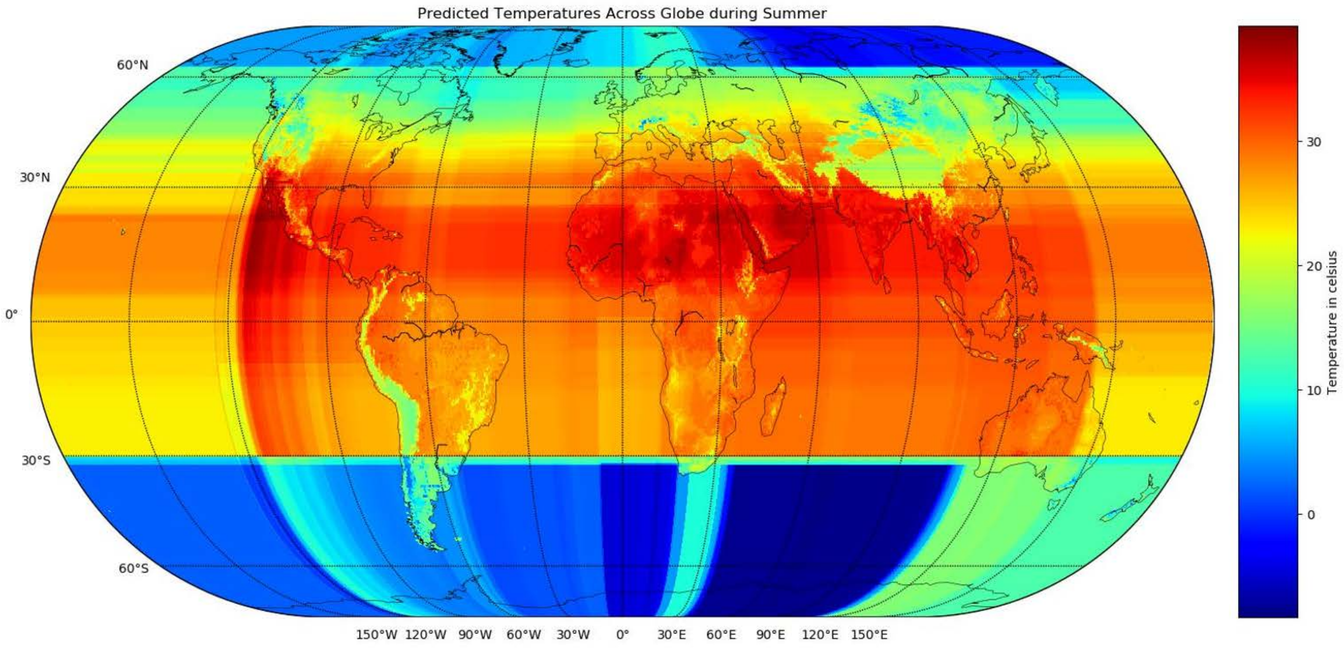
Andrew Wesson – Decision Tree



Manjur Patowary

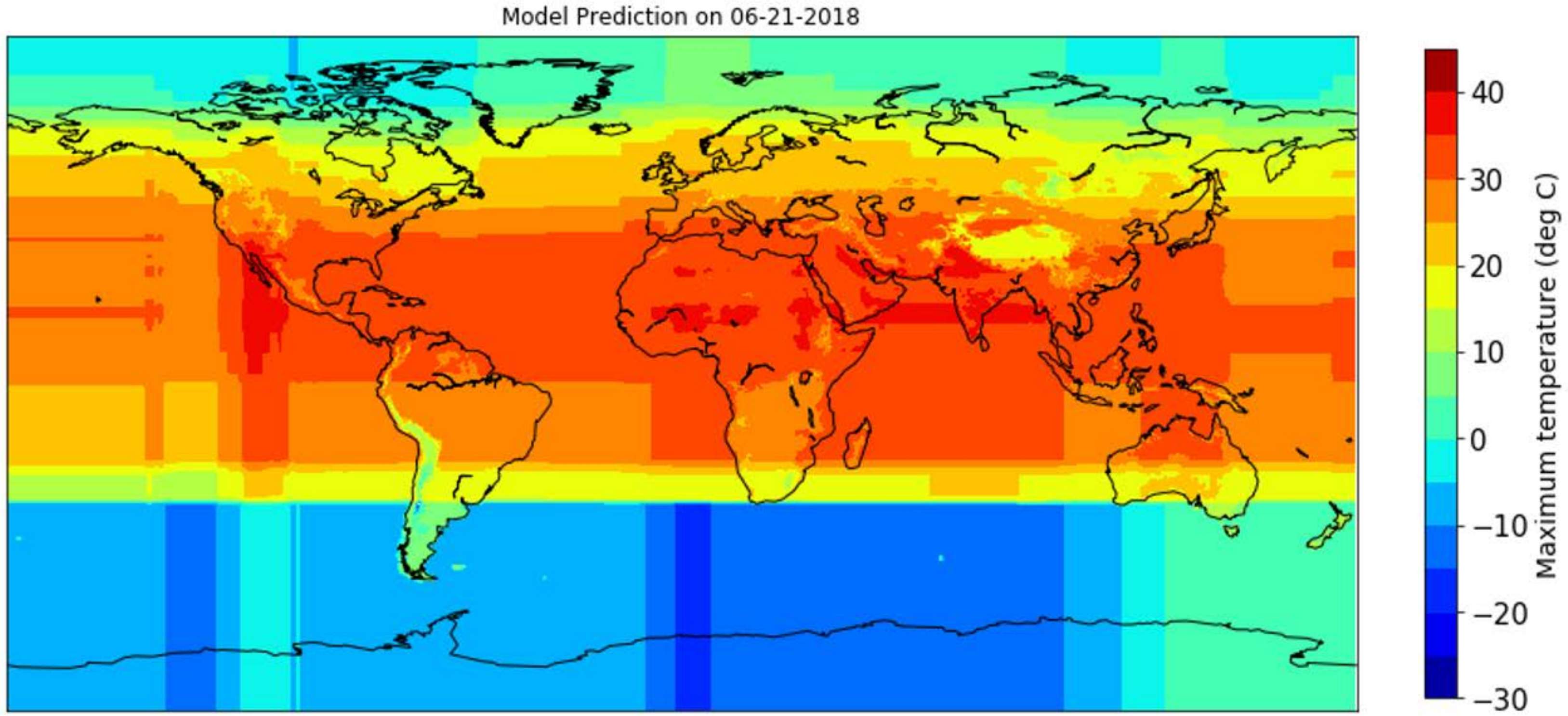


Venkata Sai Pavan Kumar Kosaraju

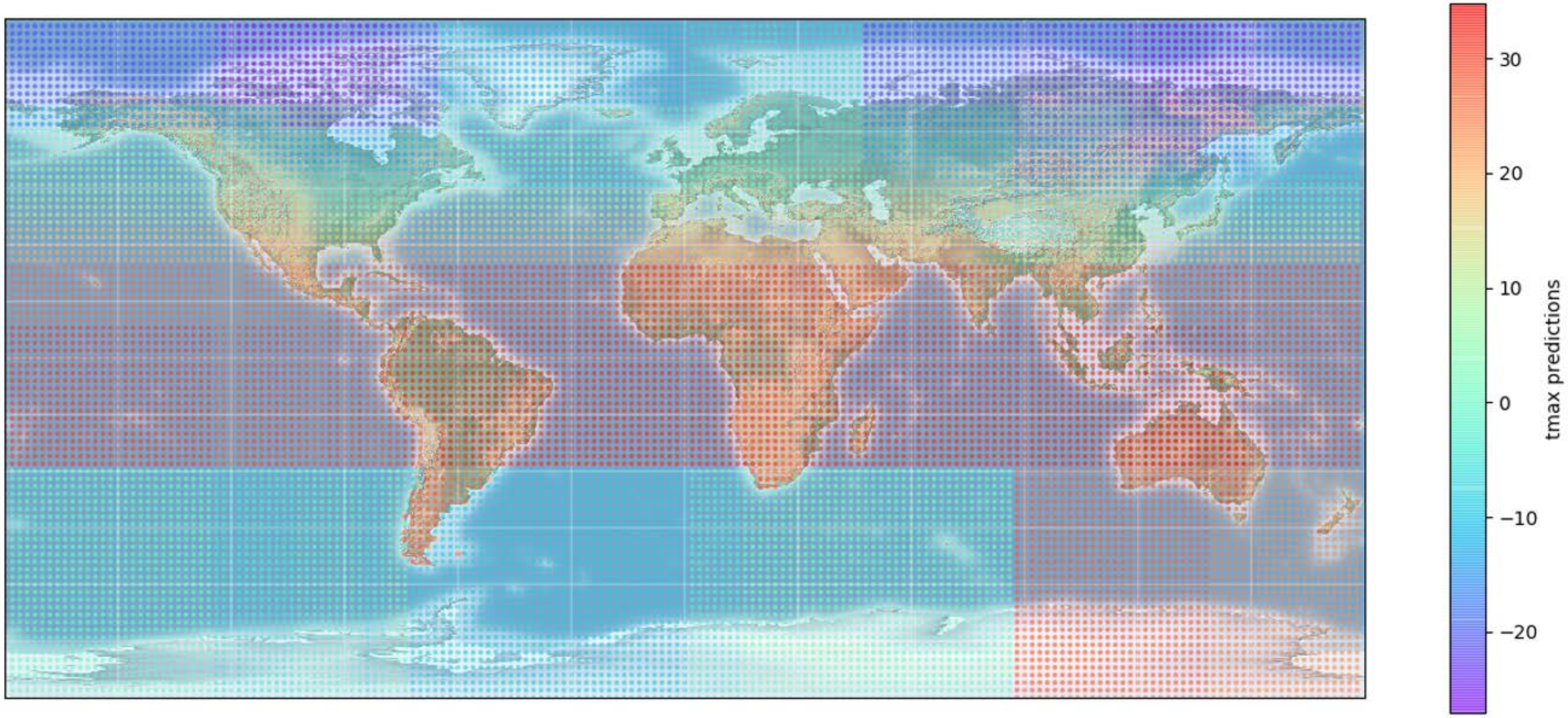


Interpretation: Predicted temperatures on 27th May 2019 across globe by the model. Temperatures may reach as high as 35 degrees near equator region while in Northern and Southern hemisphere it will be cool.

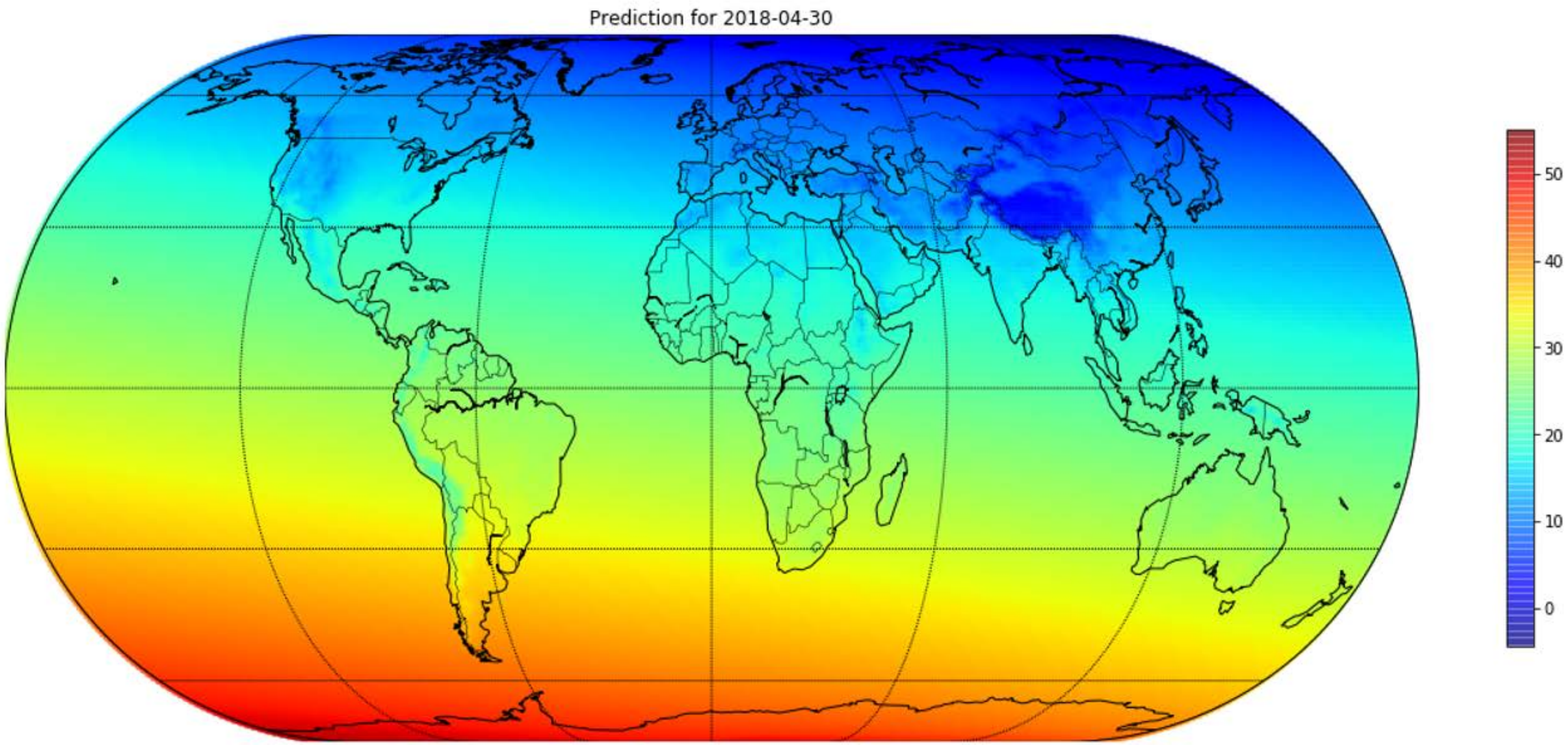
Prashanth Rao - Great discussion!



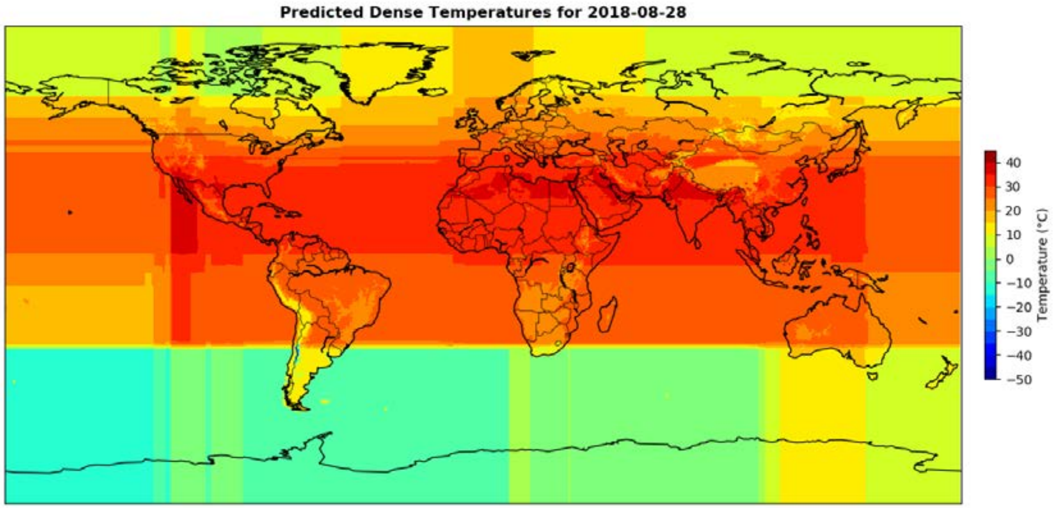
Neda Zolaktaf

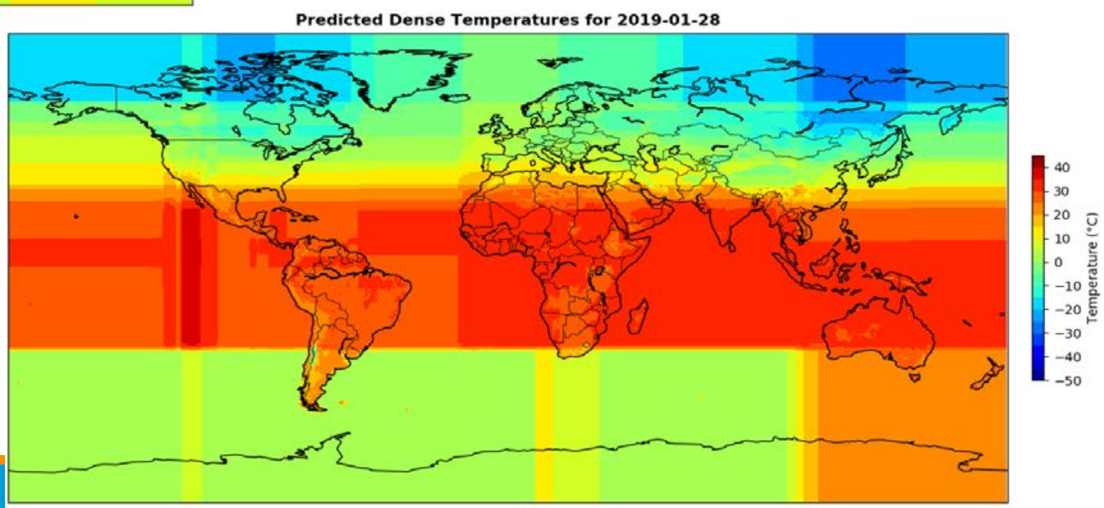


Mohammad Mazraeh



Oluwaseyi (Seyi) Talabi





Thank you for your attention!