Contextual Bandits Data Visualization

with Jupyter Notebooks

RLOS 2020

Quick Introduction

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- Program : Bachelor's/Master's in Computer Science
- School : Johns Hopkins University
- Mentors : Marco Rossi, Paul Mineiro

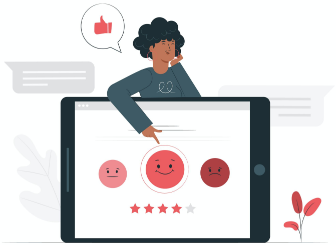
Why do we even need contextual bandit visualizations?

- Good exploratory data analysis + relevant data visualization:
    - Allows you to kickstart your analysis by easily understanding the patterns in your data
    - Helps you inspect/probe policies visually to understand their behaviour

- Visualizations are a powerful yet easily digestible way to understand your data, policies, and results well!

Vectors designed by Freepik

Who may want to use this library?



Customers
A presentable and well-documented visualization library can prove to be useful to customers to better understand their data and policies.

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Independent Researchers
Graphics that are easy to understand and use can prove to be helpful for independent researchers exploring contextual bandits through pyVW

Microsoft

MSR Researchers and Investigators
A robust toolkit capable of working with varying Vowpal Wabbit formats can prove to be useful for MSR Researchers for the variety of experiments they run with CB

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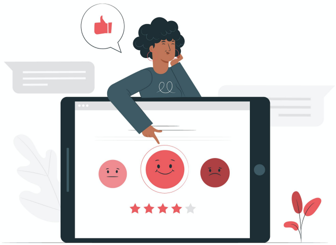
What considerations should we keep in mind?



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Initially Proposed Goals for RLOS Project

The initial call for proposals for this project contained the following goals:

- Feature importance
- Action distributions
- Action/reward distribution by feature(s) or model used
- Model comparison

Refined Goals and Workflow

1

Exploration

- Feature correlations
- Hierarchical relationships between features
- Prune your dataset to build faster learners

2

Policy Training

- Expected reward
- Comparing different trained policies
- Comparing policy to baseline

3

Feature Importance

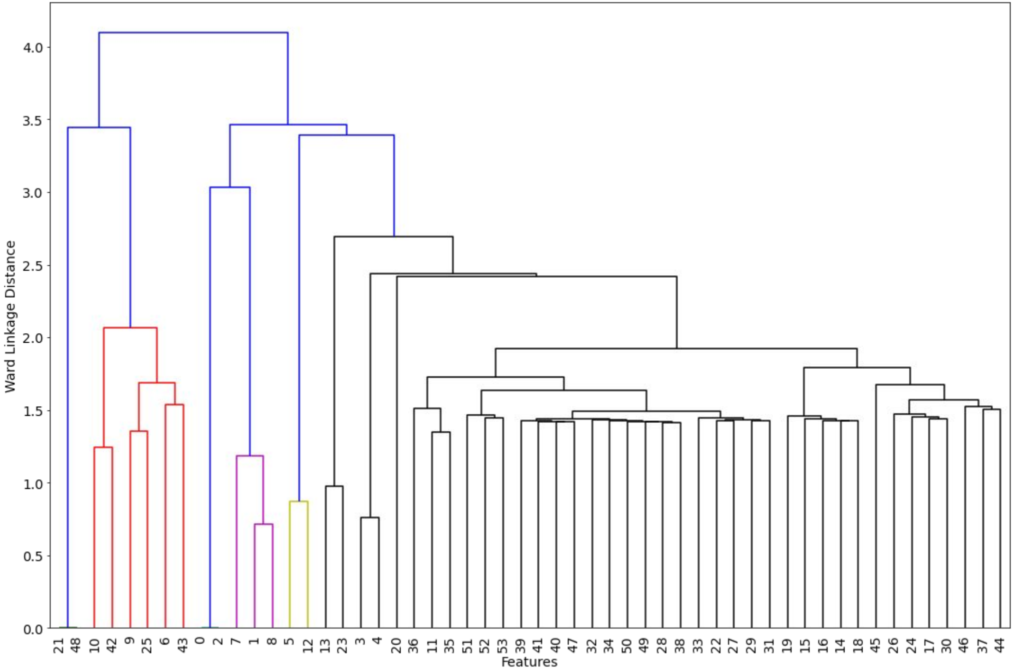
- Compare features importances
- Highlight most important features in a trained policy

4

Action Distributions

- Action set distributions in your policy

Exploration: Correlations and Hierarchy of Features



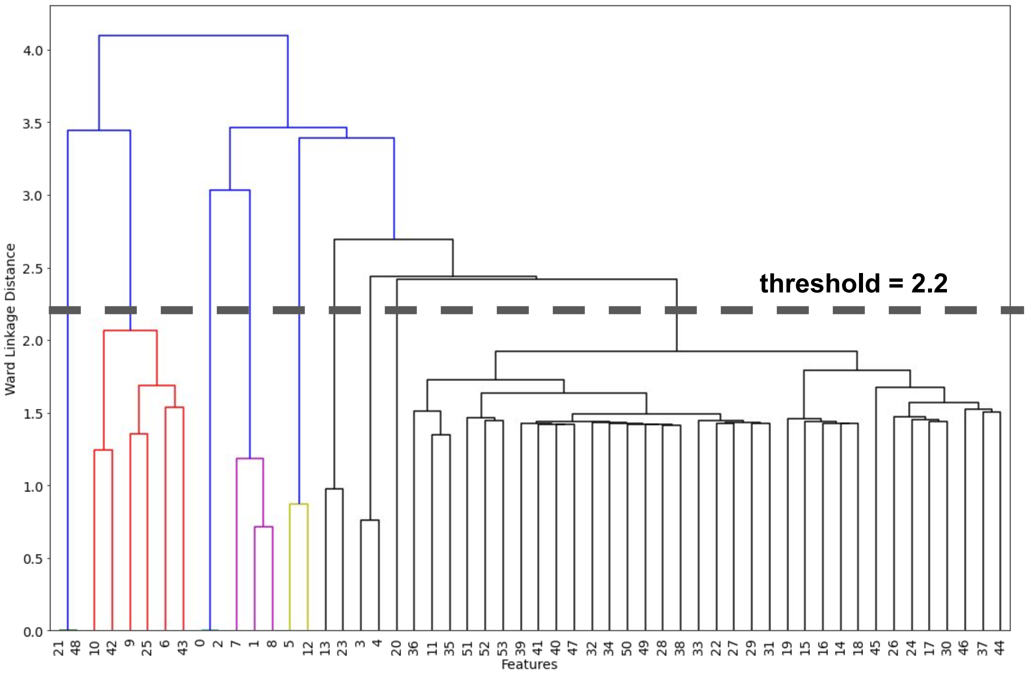
Key Points:

This is a dendrogram (tree-based diagram) illustrating relationships (y-axis) between features (x-axis)

You can use this plot to:

- Visualize hierarchical correlations between your features
- Identify clusters of closely related features
- Prune your dataset based on correlation

Exploration: Pruning Data for Correlations



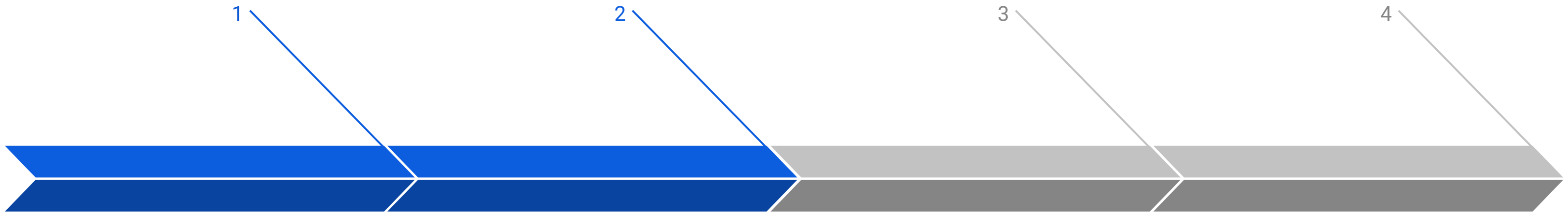
Key Points:

In this graphic, we set an illustrative threshold of 2.2 to prune the dataset's features

This is useful:

- To help policy learn faster by reducing dataset size
- To remove redundant features by clustering

Refined Goals and Workflow



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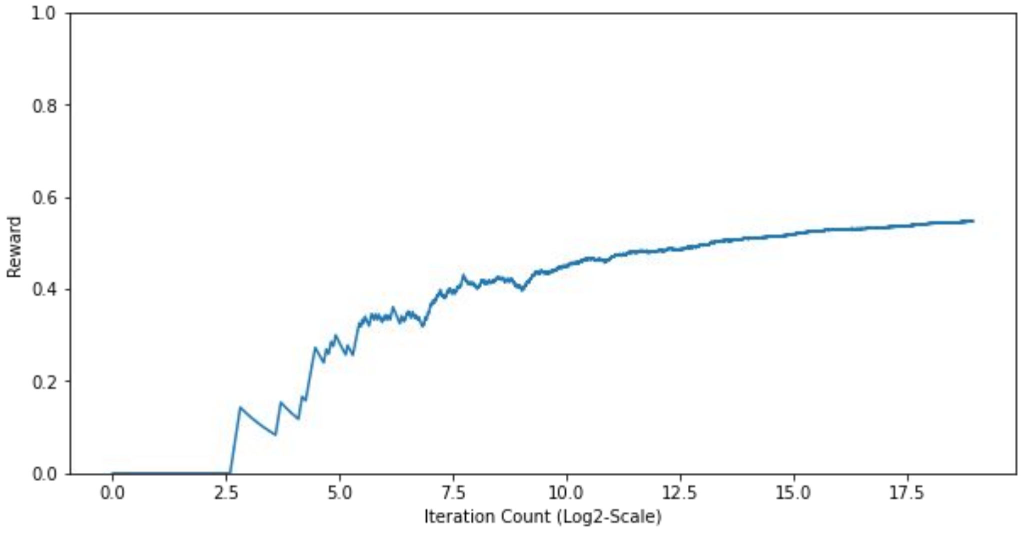
Policy Training: Expected Reward

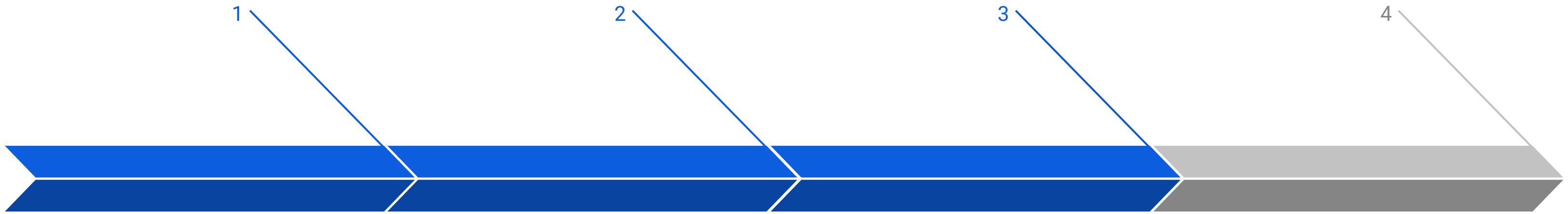


Key Points:

With this visualization, you can look at expected reward for your policy during training
This is useful:

- To gauge example size that allows your policy to learn well enough
- To highlight variation in the policy's learning as it sees more examples

Refined Goals and Workflow



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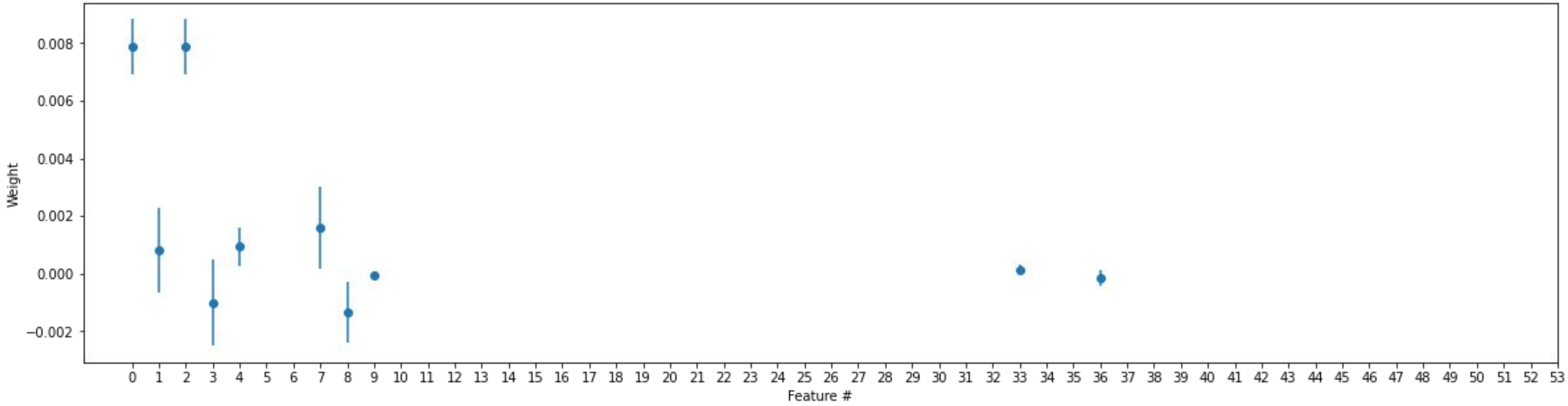
Feature Importance: Compare Feature Importances



Key Points:
This feature importance chart shows importance scores along with deviation (y-axis) for all features in the dataset (x-axis). It uses the permutation-based algorithm. By using this algorithm:

- You introduce noise
- You corrupt the value of that feature for each example
- The feature can no longer provide valuable information to the policy

This allows us to measure importance of that feature.

Feature Importance: Permutation-Based Metrics

	0	1	2	3	4	5	6
0	2596.0	51.0	5192.0	258.0	0.0	-5.0	221.0
1	2590.0	56.0	5180.0	212.0	-6.0	-5.0	220.0
2	2804.0	139.0	5608.0	268.0	65.0	-5.0	234.0
3	2785.0	155.0	5570.0	242.0	118.0	-5.0	238.0
4	2595.0	45.0	5190.0	153.0	-1.0	-5.0	220.0

Key Points:

By shuffling the values of a feature:

- You introduce noise
- You corrupt the value of that feature for each example
- The feature can no longer provide valuable information to the policy

Feature Importance: Multicollinearity Caveat

Key points:

Let’s say features 2 and 4 are correlated with each other.
Feature 2 is shuffled → policy uses feature 4 for information → feature 2 **not important!**
Feature 4 is shuffled → policy uses feature 2 for information → feature 4 **not important!**

	0	1	2	3	4	5	6
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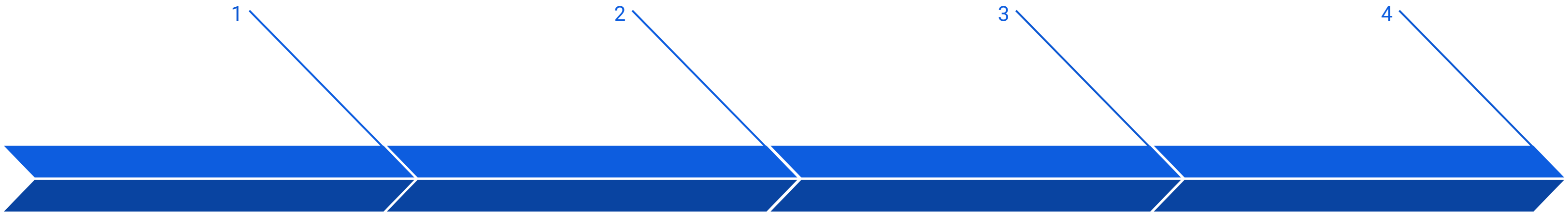

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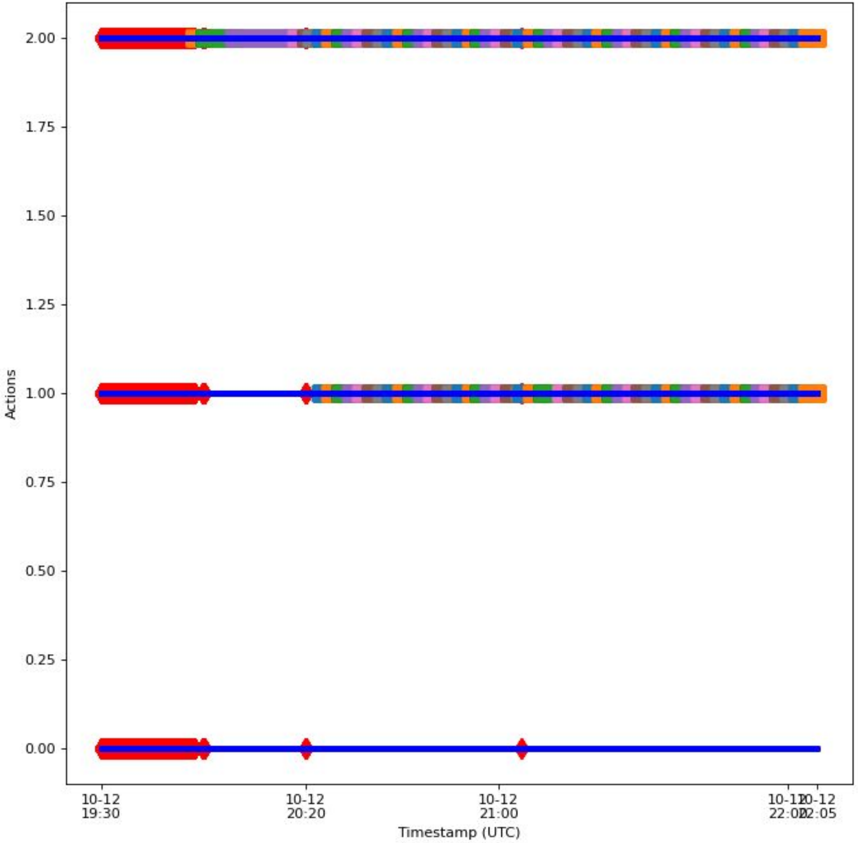
Action Distribution: Action Visualizations



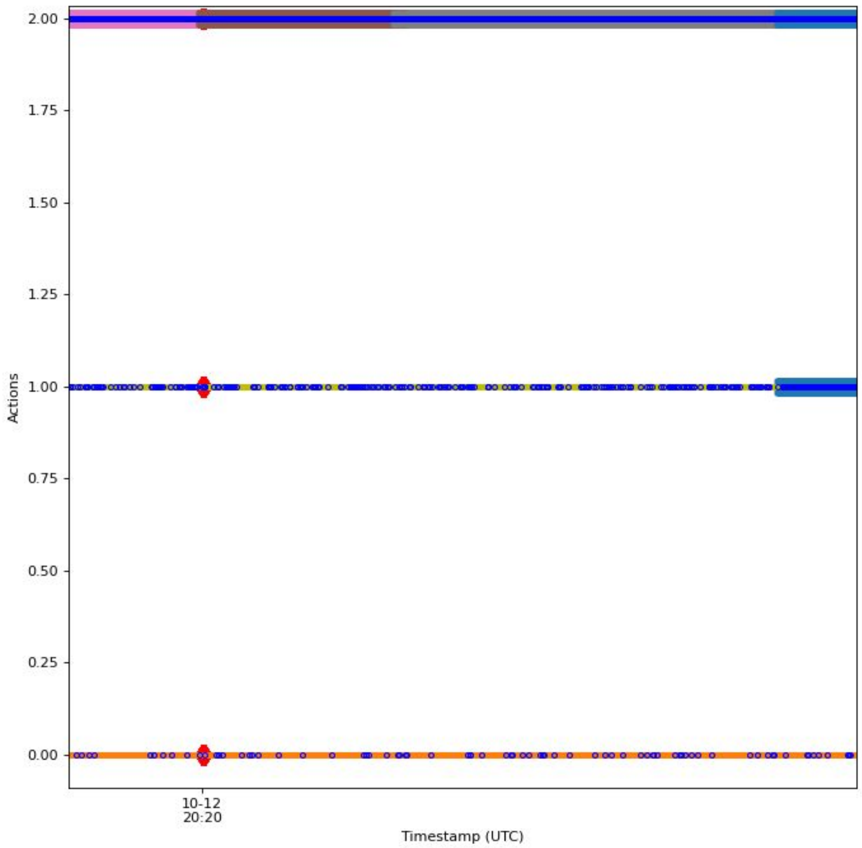
Key Points:

With this visualization, you are looking at action distributions (y-axis) and action-related metadata (colors) across all your training examples (x-axis)

Scheme:

- Red diamonds: Policy uninstantiated
- Blue: Action available in action set
- Colored squares: model available, colored based on reward

Action Distribution: Action Visualizations



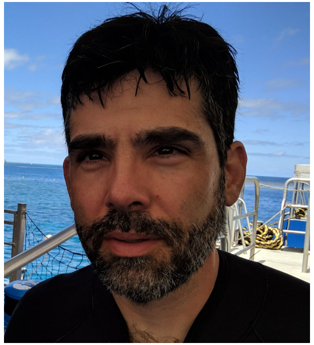
Key Points:

You can also zoom into this graphic and look at more fine-grained information.

Now, we can also see:

- Blue circles: Exact instances of reward
- Orange: colored action (baseline)

Thank you!



Marco Rossi **Paul Mineiro** **Jack Gerrits**

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