SAEfarer User Study

Introduction, tutorial, and interview slides

Introduction

- We have developed an interactive visualization tool called SAEfarer for exploring concepts learned by text classification models
- SAEfarer runs in Jupyter notebooks
- We are evaluating this tool with machine learning researchers

Agenda

- Sparse autoencoder overview (~5 min.)
- SAEfarer tutorial (~20 min.)
- SAEfarer practice (~20 min.)
- Model exploration (~30 min.)
- Questionnaire and interview (~15 min.)

Sparse Autoencoders

Sparse autoencoders (SAEs)

- SAEs are a technique for interpreting transformer-based language models
- It is difficult to interpret an LM's neuron activations
- Train an SAE to project the neuron activations at a chosen layer in the LM to a sparse, higher-dimensional space that is easier to interpret
- Each dimension of this new space ideally represents a single, human-understandable concept
- These dimensions or concepts are referred to as features of the SAE

Sparse autoencoders (SAEs)

- The goal of the SAE is to identify interpretable features used by the model
- When an instance is input to the model, every token will activate a small number of the SAE features
- The activation value of an SAE feature represents the strength of the presence of the given concept in that token
 - If a feature's activation value is 0 for a given token, then the concept is not present in that token

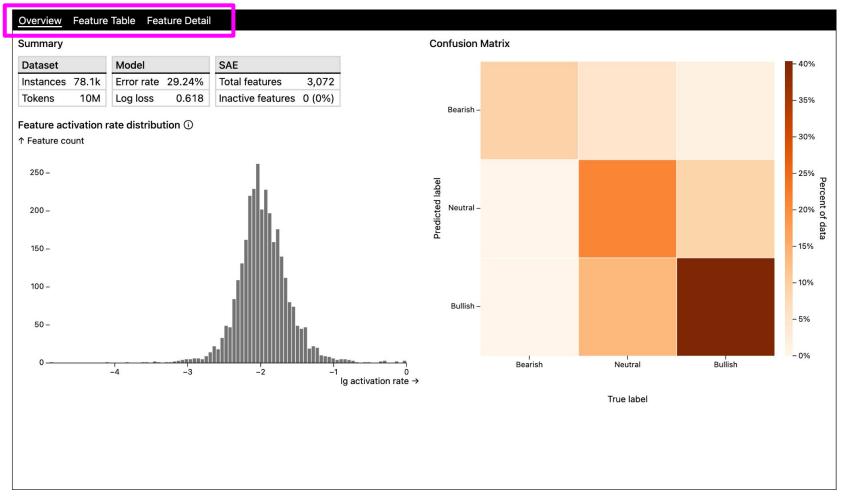
Sparse autoencoders (SAEs)

- The goal of the SAE is to identify interpretable features used by the model
- Text classification:
 - Each data point or instance is a piece of text that is represented by a series of tokens
 - Each instance has a ground truth label
 - When the model makes a prediction, it assigns a probability to each class
- We are interested in exploring the relationship between the SAE features and the model's predictions
 - What instances cause a given feature to activate?
 - Are there any trends in the model's predictions on those instances?

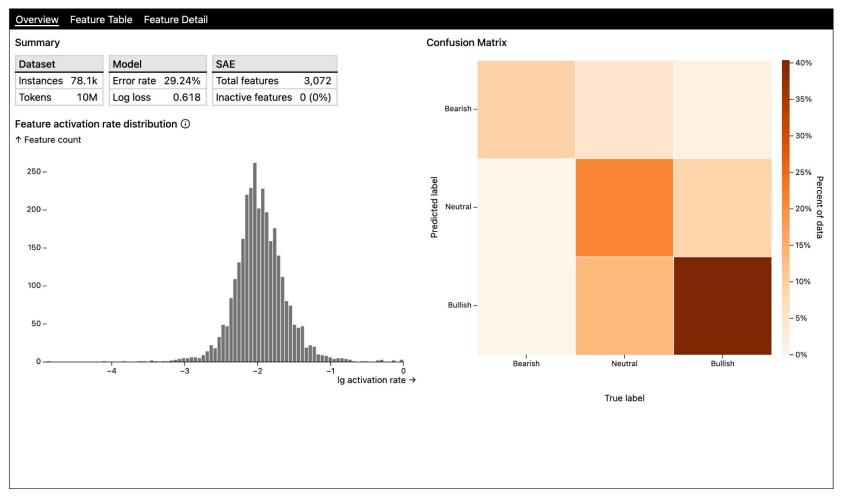
SAEfarer Tutorial

SAEfarer

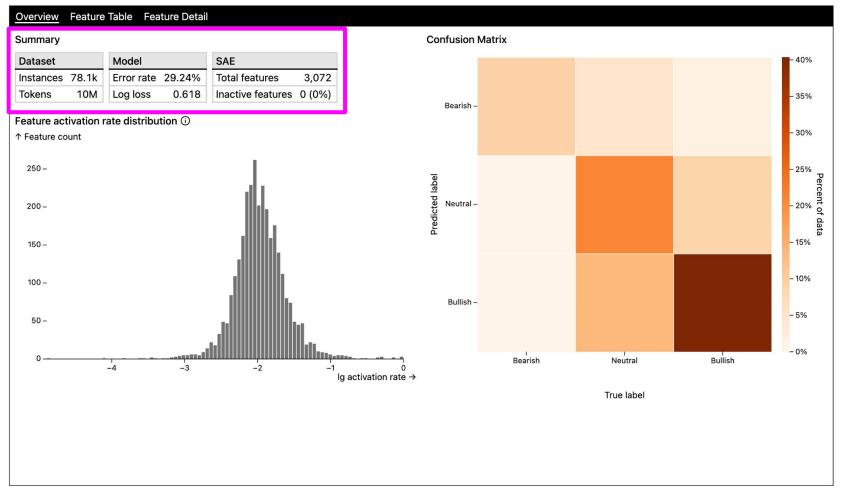
- Interactive visualization tool that runs in Jupyter notebook
- Analyzing text classification models
- Exploring the relationships between the SAE features and the model's predictions and errors
- Example
 - cryptobert: RoBERTa-based model that classifies the sentiment of cryptocurrency social media posts
 - Three classes:
 - Bearish (negative)
 - Neutral
 - Bullish (positive)



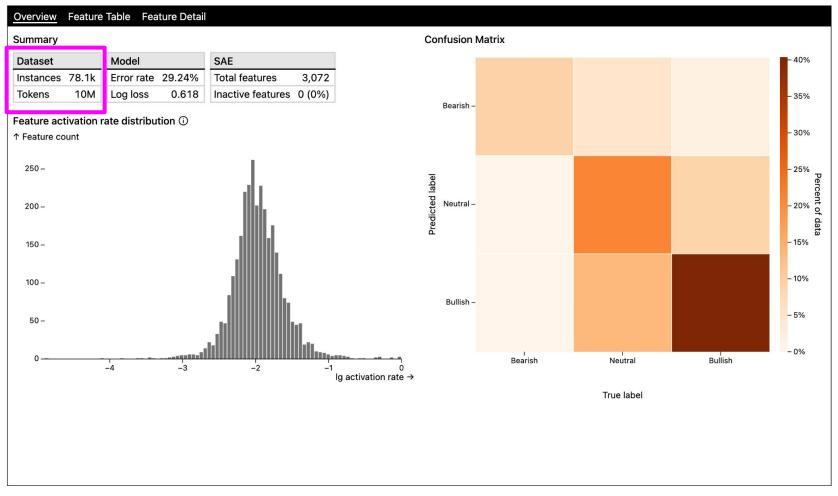
The UI has three tabs at the top.



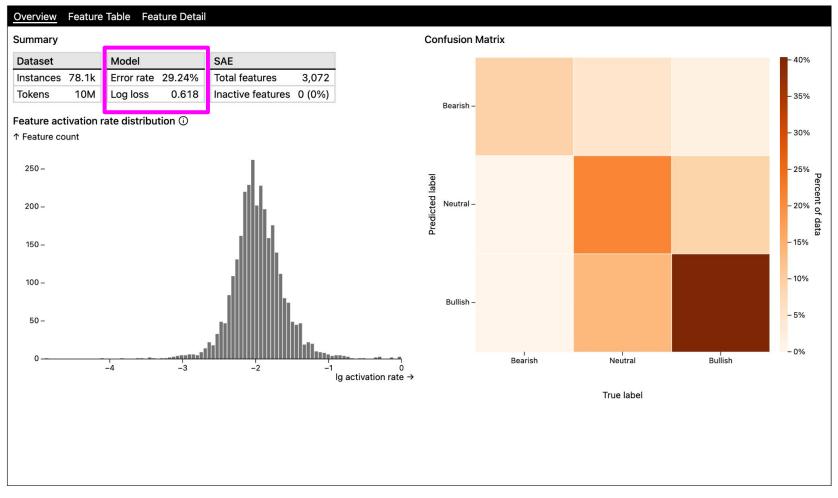
First, we'll cover the Overview tab.



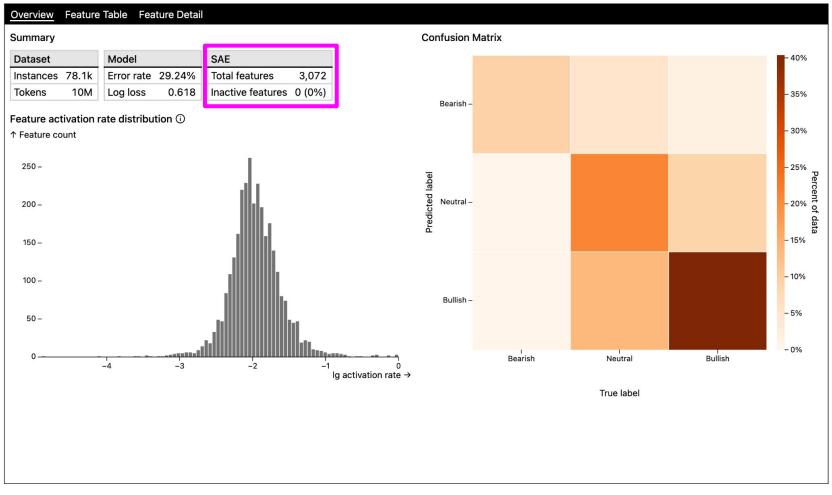
At the top, there is summary information about the dataset, model and SAE.



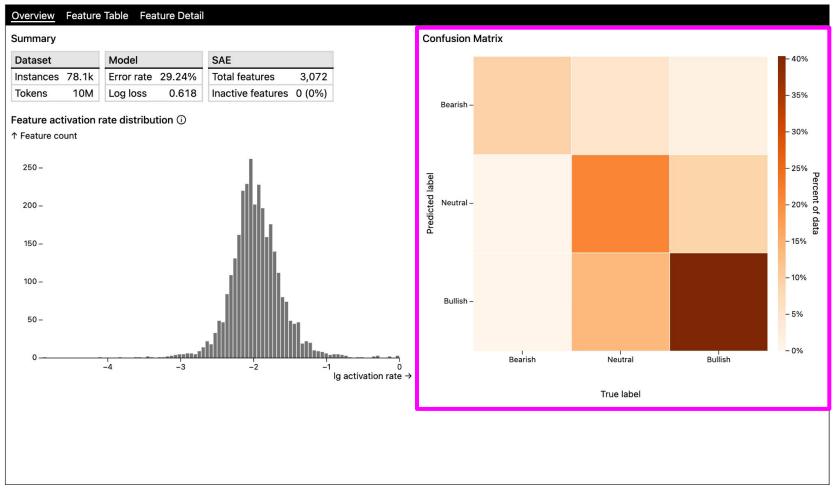
78,000 instances (10 million tokens) were used to analyze the SAE.



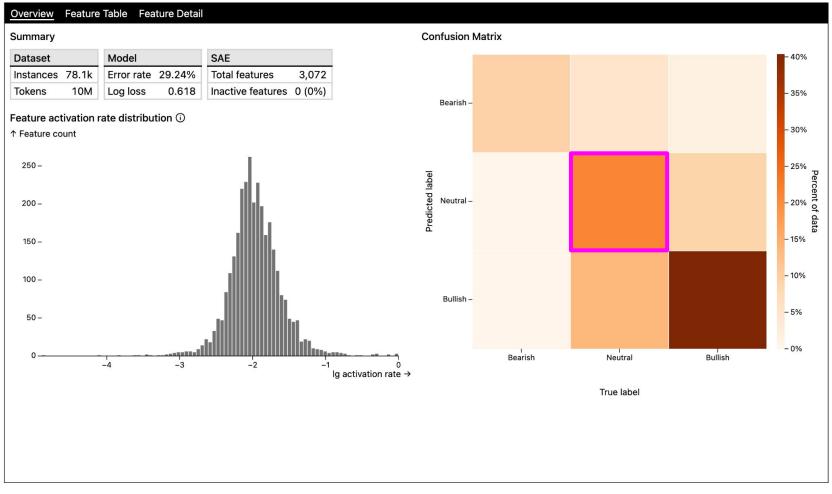
The error rate and log loss of the classification model on these instances.



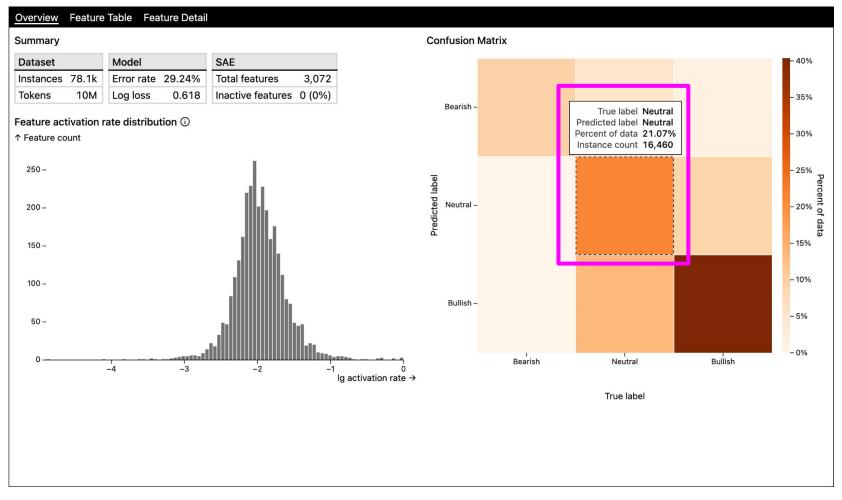
The SAE has 3072 features. All of them activated during analysis.



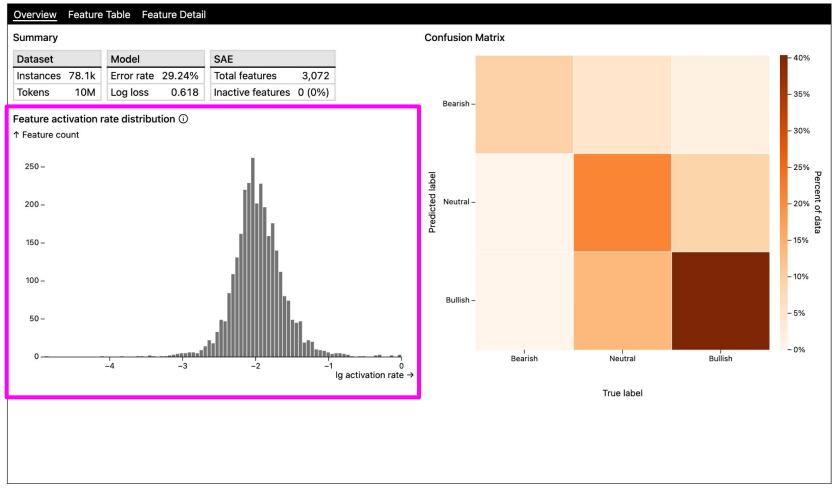
The confusion matrix shows the model's performance.



Each cell shows the percentage of instances with the given predicted and true label.



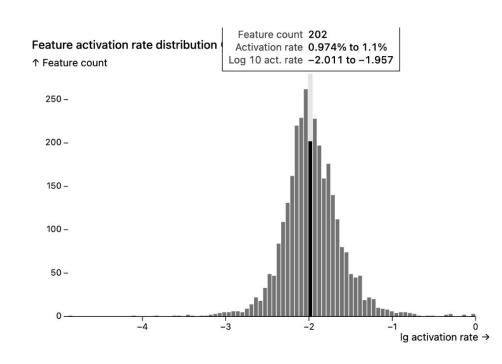
Most visualizations in SAEfarer provide details when you hover over them.

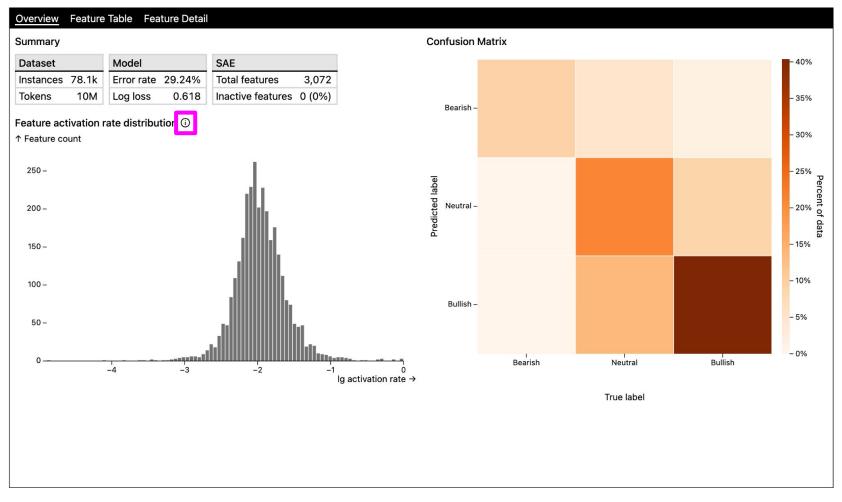


The histogram shows the distribution of how often the SAE features activated.

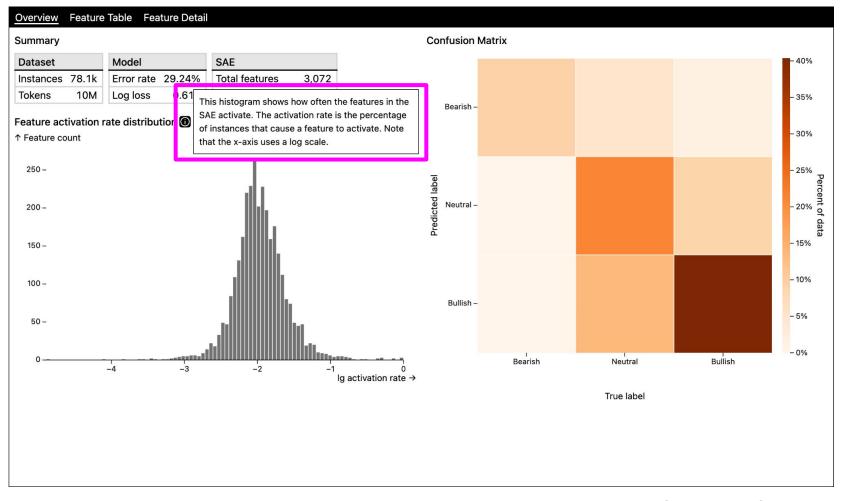
Feature activation rate distribution

- Activation rate: The percentage of instances that cause the SAE feature to activate.
- This histogram uses a log10 scale on the x-axis.
 - 10% act. rate = -1 lg act. rate
 - 1% act. rate = -2 lg act. rate
- Example: 202 features activate on 0.974% to 1.1% of instances.

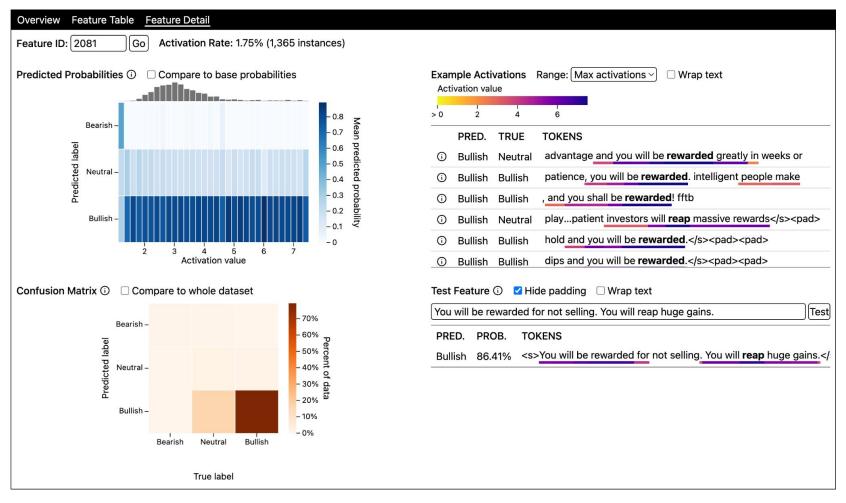




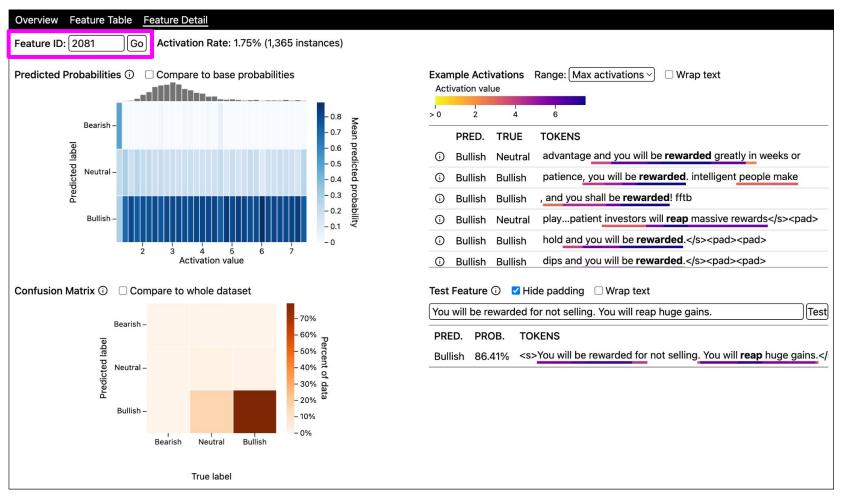
Throughout the UI, there are help icons.



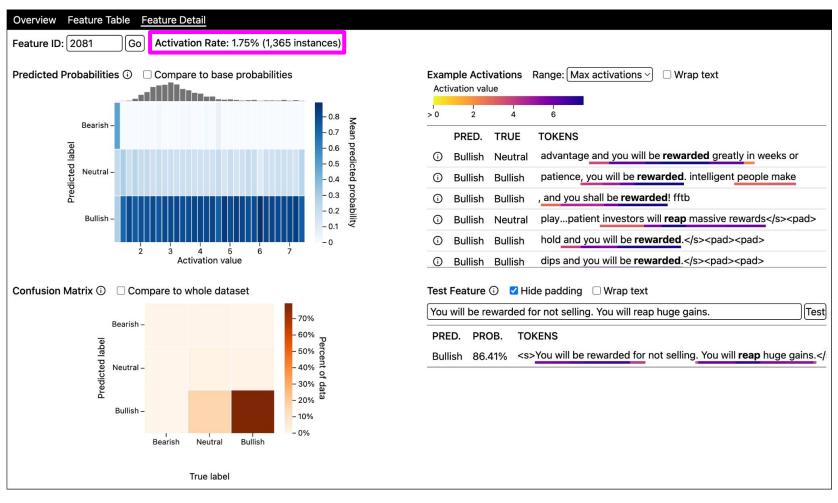
Hovering over the icon shows a tooltip that explains that part of the interface.



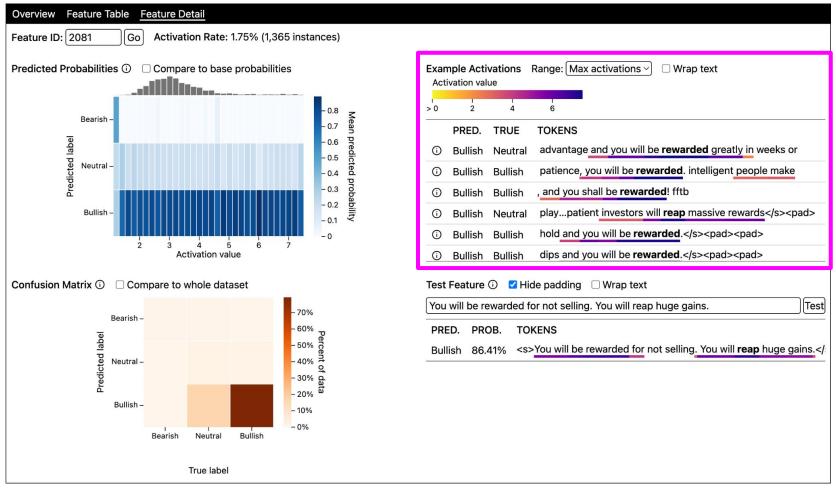
Next, we'll cover the Feature Detail tab.



At the top left, there is the ID of the currently displayed feature.



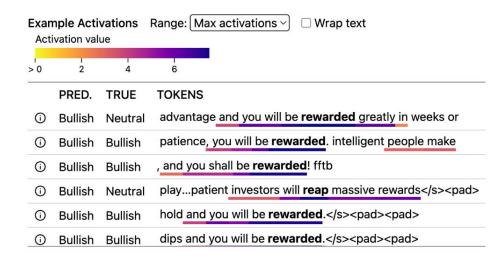
Next, there is the activation rate of this feature.



In the top right, we show snippets of the instances that activate the feature the most.

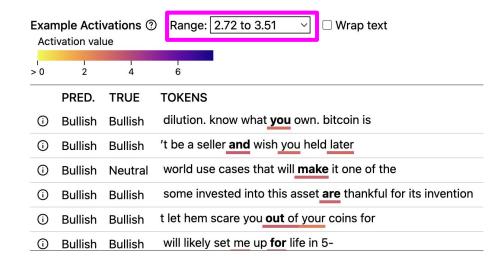
Example Activations

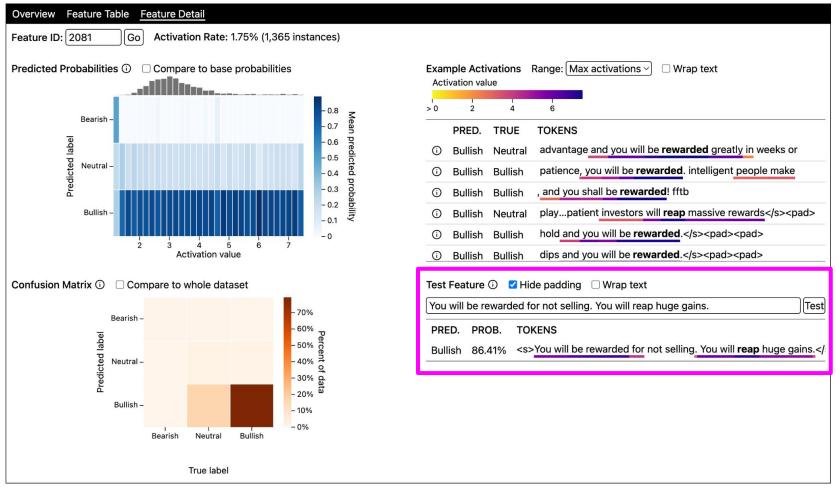
- The colored line beneath a token encodes the feature's activation value on that token.
- The token with the highest activation in the instance is also bolded.
- The 5 tokens before and after this token are provided as context.
- The table shows the predicted and true label for each instance.
- The information icon provides additional details about the instance.
- This table scrolls.



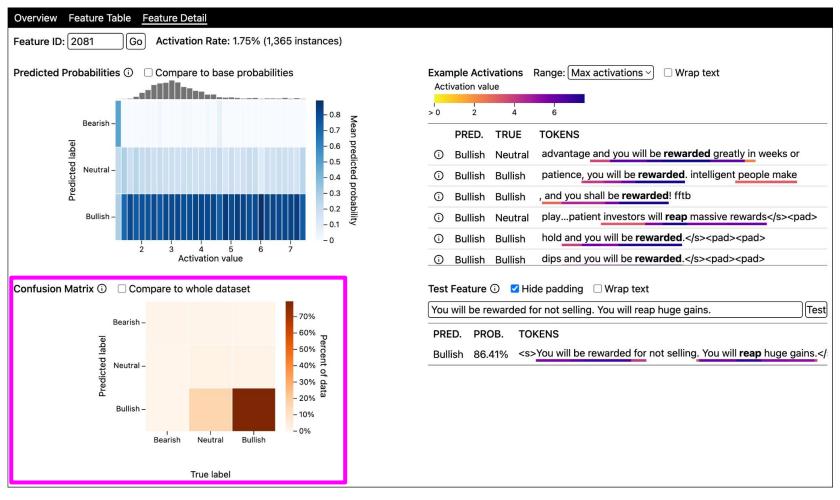
Example Activations

- By default, the instances with highest activations are shown.
- Adjusting the range lets you examples across the distribution of activation values.

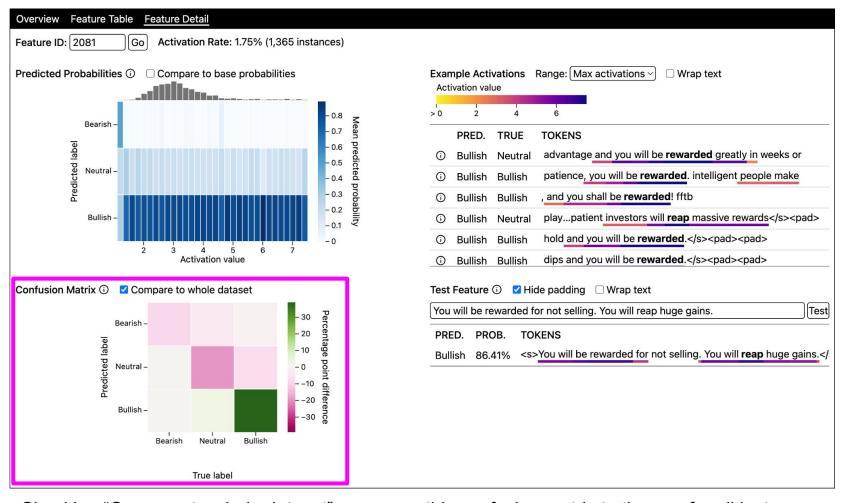




In the bottom right, you can enter your own text and check if it activates the feature.



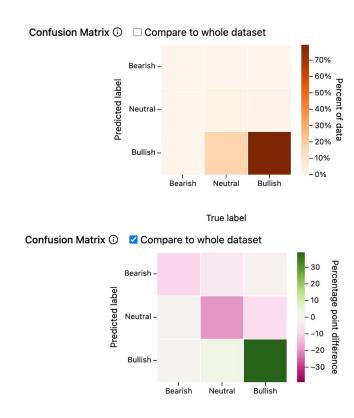
The confusion matrix shows the model's performance on instances that activate this feature.



Checking "Compare to whole dataset" compares this confusion matrix to the one for all instances.

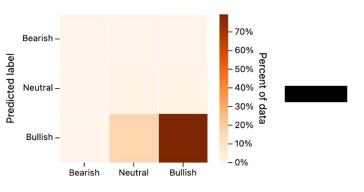
Confusion matrix comparison

- How do the model's predictions on the instances that activate this feature compare to its predictions on the whole dataset?
- Calculate the percentage point difference between the cells of this confusion matrix and the one for all instances.
- Ex: The model predicts Bullish more often on the instances that activate this feature than on the whole dataset.



True label

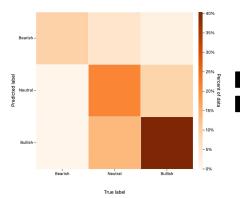
Confusion matrix from the Feature Detail tab.



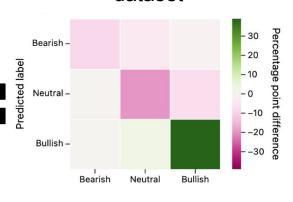
True label

Calculated from instances that activate the feature.

Confusion matrix from the Overview tab.



Comparison to whole dataset



True label

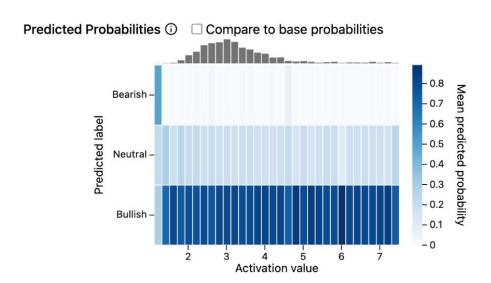
Calculated from all instances



The top left shows the model's predicted probabilities on the instances that activate this feature.

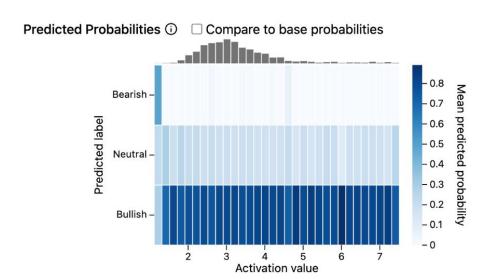
Predicted Probabilities

- What is the relationship between the feature's activation value and the model's predictions?
- Bin the instances that activate the feature by their maximum activation value
 - Multiple tokens in an instance can cause the feature to activate.
 - Across all of the tokens in the instance, take the maximum activation value.
- Calculate the model's mean predicted class probabilities for each bin.



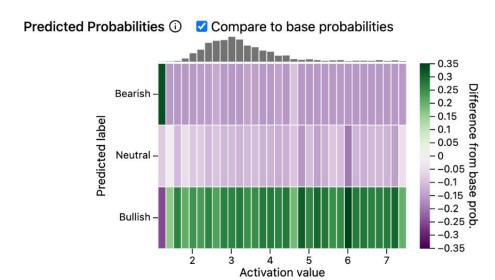
Predicted Probabilities

- Visualized with a heatmap.
- Each row represents a class.
- Each column represents a range of activation values.
- The color of a cell encodes model's mean predicted probability for the given class for instances that activate the feature in the given range.
- This histogram above the heatmap shows the number of instances in each activation value bin.
- Ex: The model assigns a high probability to Bullish for all activation value bins except the lowest.



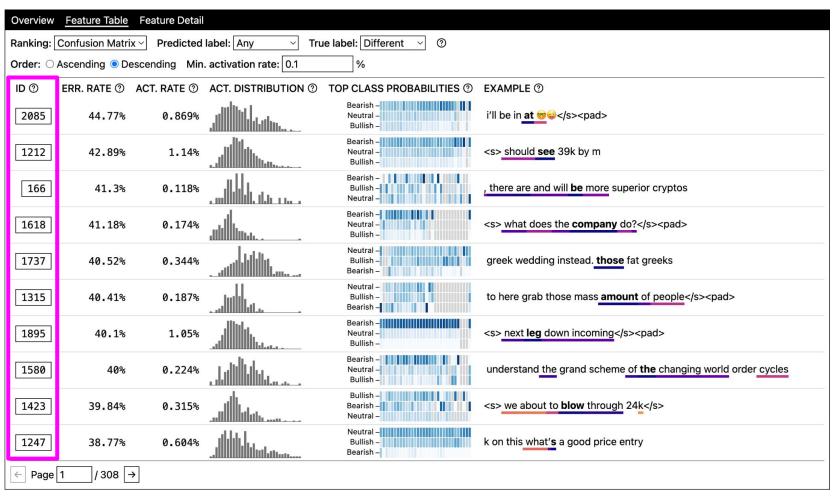
Predicted Probabilities

- Checking "Compare to base probabilities" subtracts each row by the mean predicted probability for that class across all instances.
- This highlights how the model's predicted probabilities on the instances that activate this feature differs from its predicted probabilities on the entire dataset.
- Ex: the model assigns higher probability to Bullish for these instances than it does for the dataset as a whole.

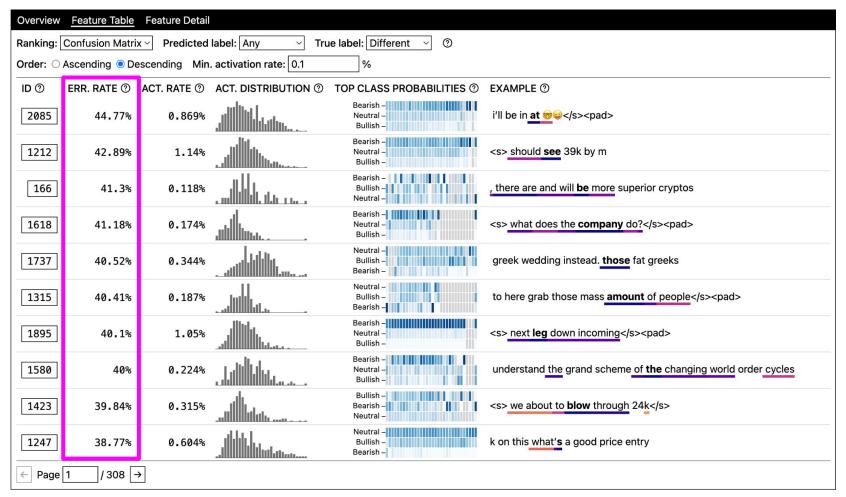




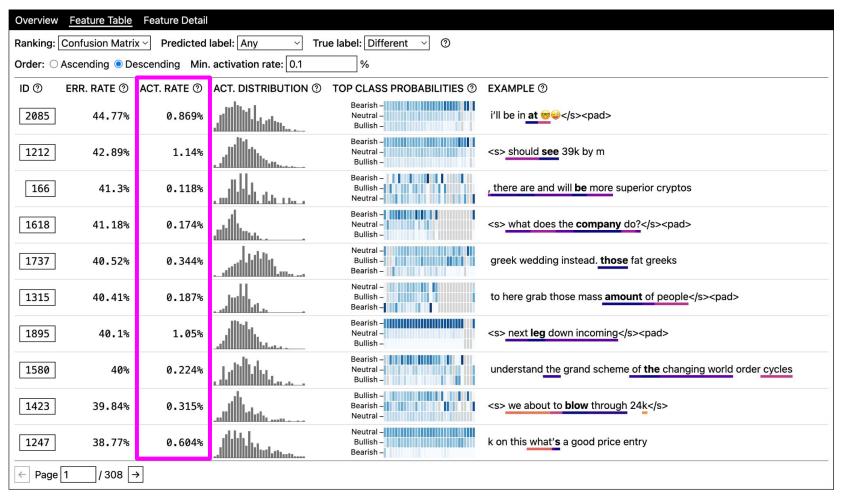
Finally, we will cover the Feature Table tab.



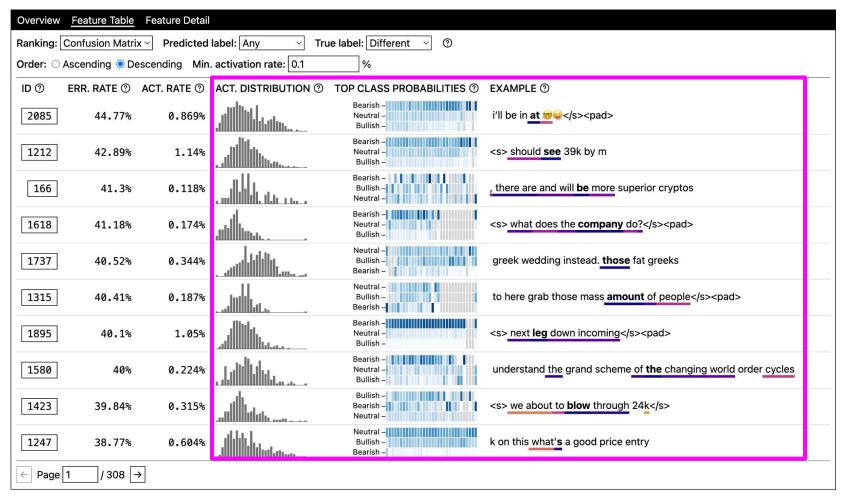
The 1st column contains the ID of the feature. Clicking the ID goes to the Feature Detail tab.



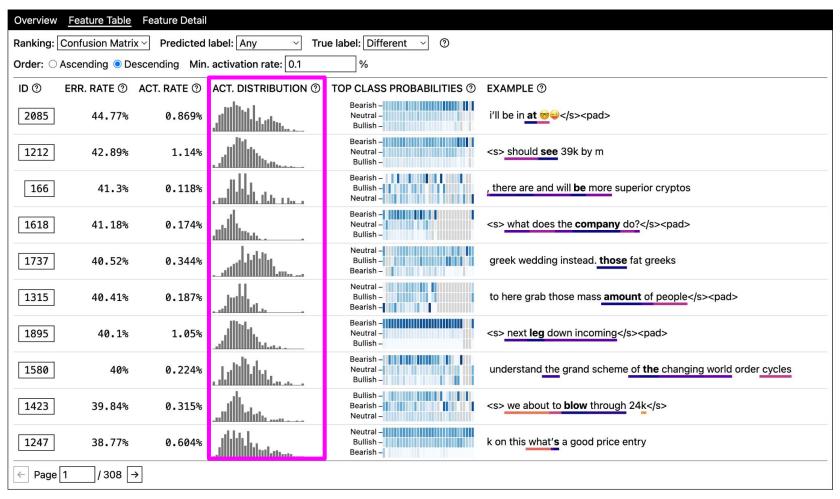
The 2nd column shows the model's error rate on the instances that activate the feature.



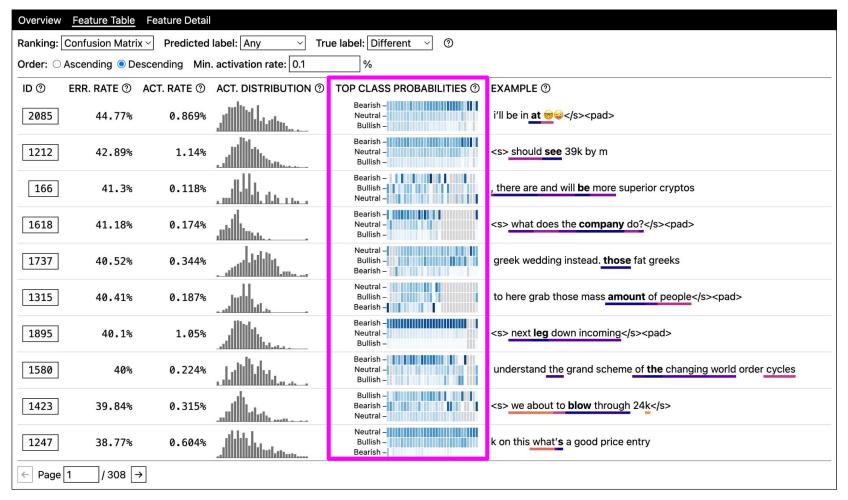
The 3rd column shows the feature's activation rate.



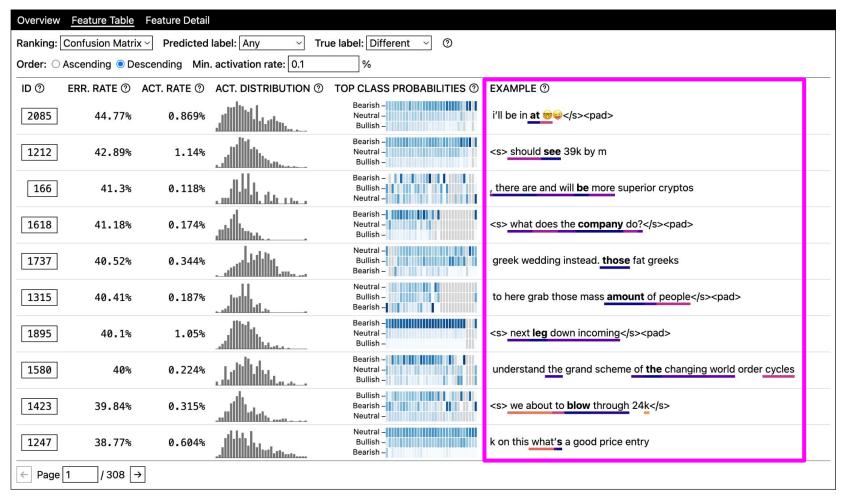
The remaining columns are visualizations that are also on the Feature Detail tab.



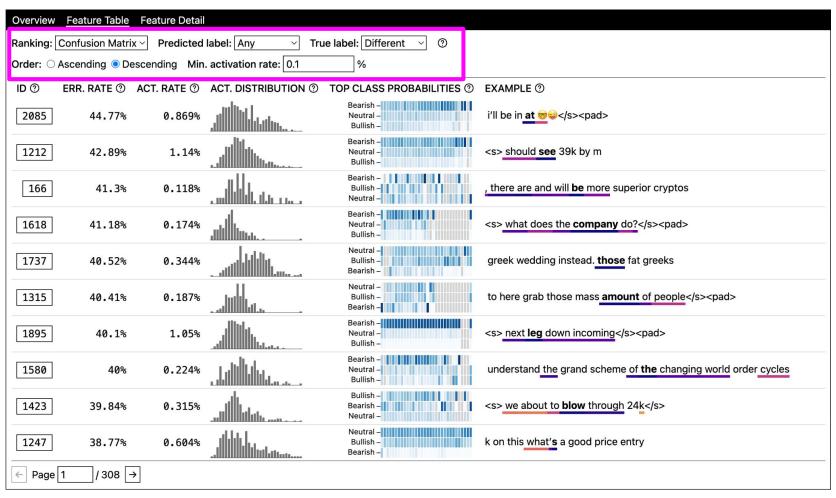
The 4th column shows a histogram of the activation values.



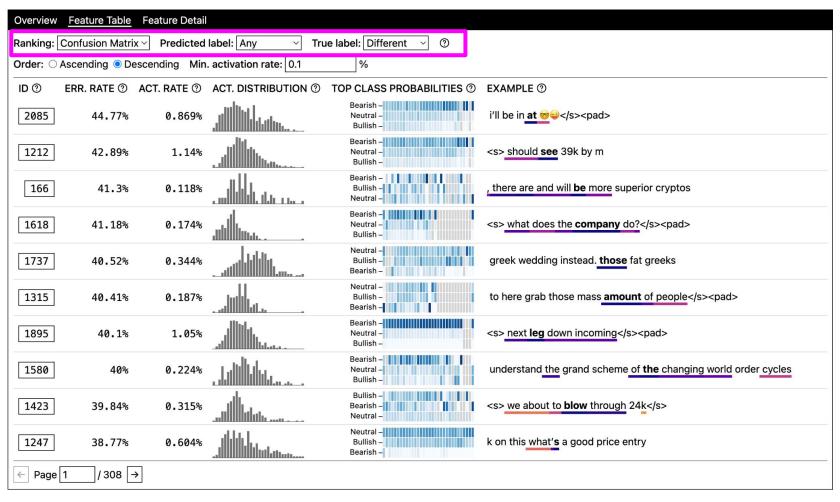
The 5th column shows the model's predicted probabilities for the top 3 classes.



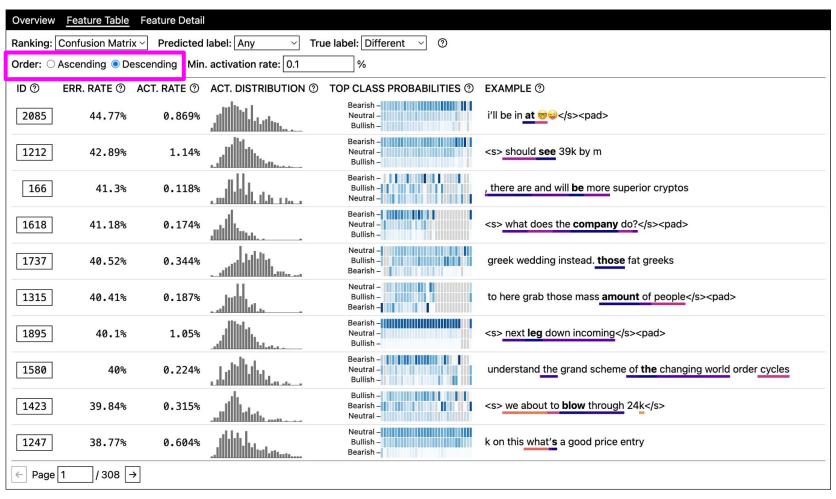
The last column shows the sequence of tokens that maximally activates the feature.



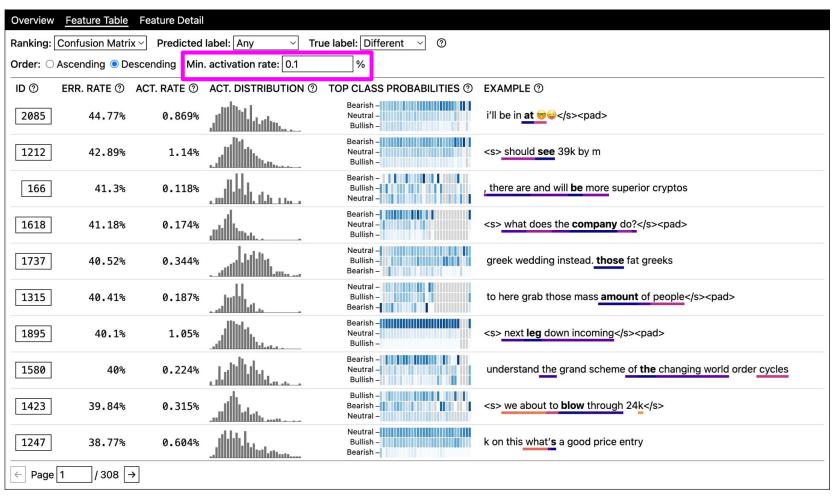
At the top of the tab, you can control how the features are sorted and filtered.



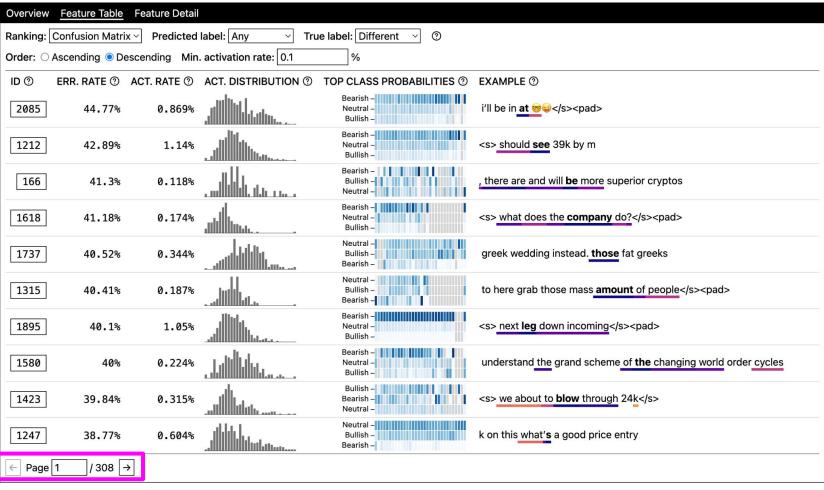
The first row of controls sets ranking method.



In the second row, you can choose between ranking in ascending or descending order.



You can filter the features by setting a threshold for the minimum activation value.



At the bottom of the tab, you can change the page of the table.

Feature Ranking

Three ways to rank the features:

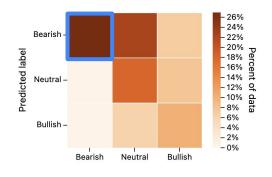
- ID
 - Index of the feature in the SAE.
 - This is basically a random order.
- Activation rate
 - How often the feature activates.
- Confusion matrix
 - The model's predictions and errors on the instances that activate the feature.

Confusion Matrix Ranking

- We calculate a confusion matrix for each feature based on the instances that cause that feature to activate.
- We can rank the features based on values derived from these confusion matrices.
- For this ranking, you choose both a predicted label and a true label.
 - This determines the value that is used to rank the features.

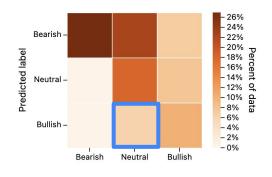
Ranking: Confusion Matrix > Predicted label: Bearish > True label: Bearish >

- Predicted label is Bearish.
- True label is Bearish.
- This ranks the features by the percentage of instances that activate the feature where the model predicts correctly predicts Bearish.



Ranking: Confusion Matrix > Predicted label: Bullish > True label: Neutral >

- Predicted label is Bullish.
- True label is Neutral.
- This ranks the features by the percentage of instances that activate the feature where the model predicts Bullish, but the true label is Neutral.



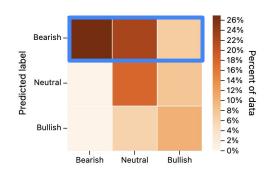
Confusion Matrix Ranking

- In addition to selecting the name of a class, you can also select the wildcard value "Any".
- This represents any of the classes.

Ranking: Confusion Matrix > Predicted label: Bearish > True label: Any

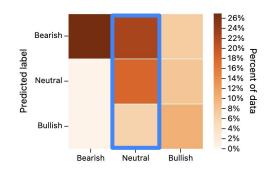
Ranking: Confusion Matrix > Predicted label: Bearish > True label: Any

- Predicted label is Bearish.
- True label is Any.
- This ranks the features by the percentage of instances that activate the feature where the model predicts Bearish.



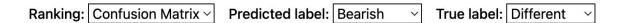
Ranking: Confusion Matrix > Predicted label: Any > True label: Neutral >

- Predicted label is Any.
- True label is Neutral.
- This ranks the features by the percentage of instances that activate the feature where the true label is Neutral.



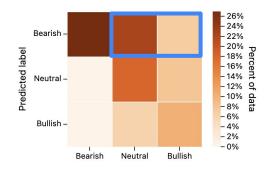
Confusion Matrix Ranking

- The second wildcard value is "Different".
- This represents any class except the other one that is selected.
- For example:
 - Predicted label is Bearish
 - True label is Different
 - Different represents Bullish or Neutral.



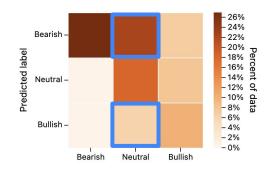
Ranking: Confusion Matrix > Predicted label: Bearish > True label: Different >

- Predicted label is Bearish.
- True label is Different.
- This ranks the features by the percentage of instances that activate the feature where the model incorrectly predicts the label to be Bearish.



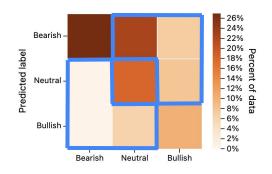
Ranking: Confusion Matrix > Predicted label: Different > True label: Neutral >

- Predicted label is Different.
- True label is Neutral.
- This ranks the features by the percentage of instances that activate the feature where the true label is Neutral and the model predicts something else.



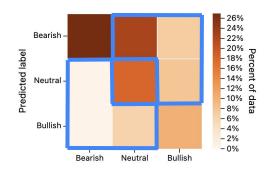
Ranking: Confusion Matrix > Predicted label: Any > True label: Different >

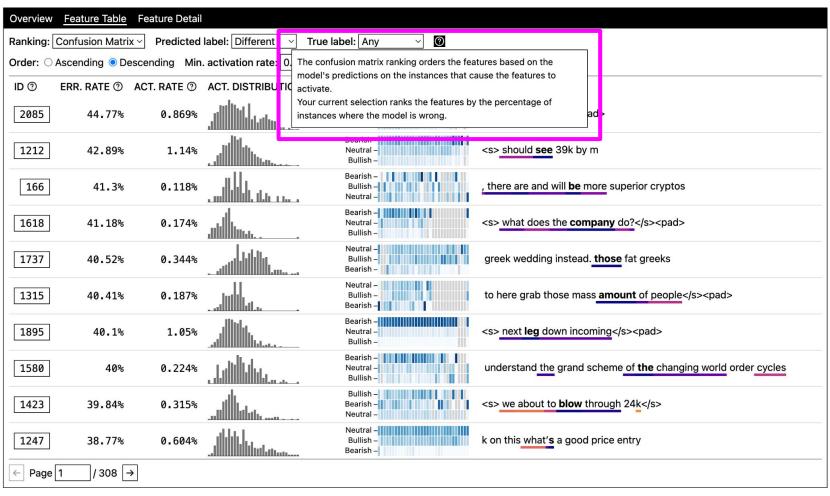
- Predicted label is Any.
- True label is Different.
- This ranks the features by the percentage of instances that activate the feature where the model is incorrect.



Ranking: Confusion Matrix > Predicted label: Different > True label: Any

- Predicted label is Different.
- True label is Any.
- This ranks the features by the percentage of instances that activate the feature where the model is incorrect. Same as previous case.





The question mark icon next to the ranking controls explains how you are currently ranking the features.

Interview

 Based on your exploration, do you have any ideas for how you might improve the model?

Did it help you to understand the behavior of the model?

How did SAEfarer support your model analysis?

Were there any questions that you were unable to answer?

In what ways did it not support your model analysis?

Were there any tasks you were unable to perform?

- Were the visualizations useful?
- Were any of them unclear?

How did you prefer to use the confusion matrix rankings?

Were the confusion matrix rankings helpful?

Was it clear how to use it?

Are there any additional ways that would be helpful to rank the features?

Are there any additional ways that would be helpful to filter the features?

What parts of the tool were the most helpful?

What aspects of SAEfarer did you like the most?

Are there any improvements or additional capabilities that you would want

What are SAEfarer's biggest weaknesses or limitations?

- SAEfarer to have?
- Is there additional information that would be helpful to provide in the tool?

)	Do you have any other feedback about SAEfarer?

Conclusion

- Thank you!
- We will send you your compensation soon.