The What-If Tool (WIT)

Interactive Probing of Machine Learning Models

•••

James Wexler, Mahima Pushkarna, Tolga Bolukbasi, Martin Wattenberg, Fernanda Viegas, and Jimbo Wilson

Presented on Nov 19, by Patrick Huber

Problem & Objective

Problem:

- Machine Learning models (e.g. deep learning) are “black-boxes”
- Responses of models to different inputs cannot be easily foreseen
- Big topic in AI: **Explainability**

Objective:

- Gain understanding of a model’s capabilities
    - when does it perform well/poorly
    - How is a change in the input reflected in the output (diversity)

Solution:

- Interactive visual “what-if” exploration

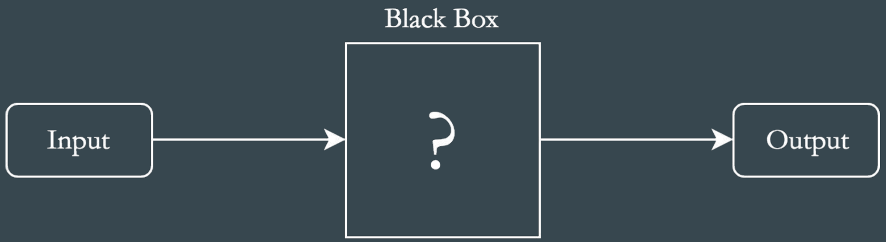
Model Understanding Frameworks

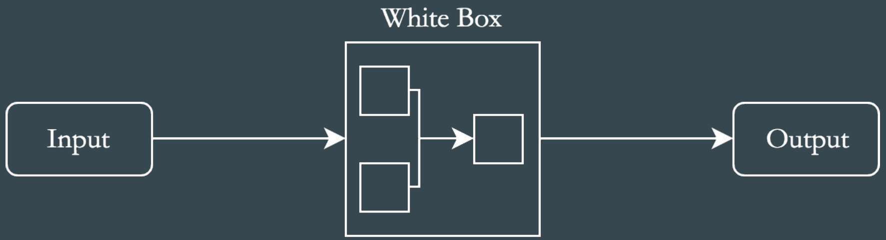
Black-Box:

- Does not rely on internals
- Probing depending on in- and outputs
- General - used in many applications
- WIT

White-Box:

- Illuminates internal workings
- Specific for a model
- Often not applicable





Why? - Initial Analysis

Proof-of-concept

- Evaluate technical suitability and compatibility of InfoVis solution

Workshops

- 2 usability studies at different scales and with different user-groups
- Application builds on insights from usability studies
- Authors derive 5 distinct user needs

Why? - User Needs

Need 1: **Test multiple hypotheses with minimal code**

- Interact with trained model through graphical interface (no code)
- Comprehend relationships between data and models

Need 2: **Use visualizations as a medium for model understanding**

- Generate explanations for model behavior
- Problem: Visual complexity, hard to find meaningful insights
- Solution: Provide multiple, complementary visualizations

Why? - User Needs

Need 3: **Test hypotheticals without having access to the inner workings of a model**

- Treat models as black boxes
- Generate explanations for end-to-end model behavior
- Answer questions like
  - "How would increasing the value of X affect a model's prediction scores?"
  - "What would need to change in the data point for a different outcome?"
- No access to model internals
- Explanations generated remain model-agnostic
- Increases flexibility

Why? - User Needs

Need 4: **Conduct exploratory intersectional analysis of model performance**

- Users often interested in subsets of data on which models perform unexpectedly
- False positive and false negative rates can be wildly different
- Negative real-world consequences

Need 5: **Evaluate potential performance improvements for multiple models**

- Track impact of changes in model hyperparameters (e.g. changing a threshold)
- Interactively debug model performance by testing strategies

What? - The Tool

Build using Tensorboard, a code-free and installation-free visualization framework

- No custom coding (N1)
- Help developers and practitioners to understand ML systems
- Covers many standpoints (Inputs / single data points / models)
- Basic layout: 2 main panels → control panel & visualization panel

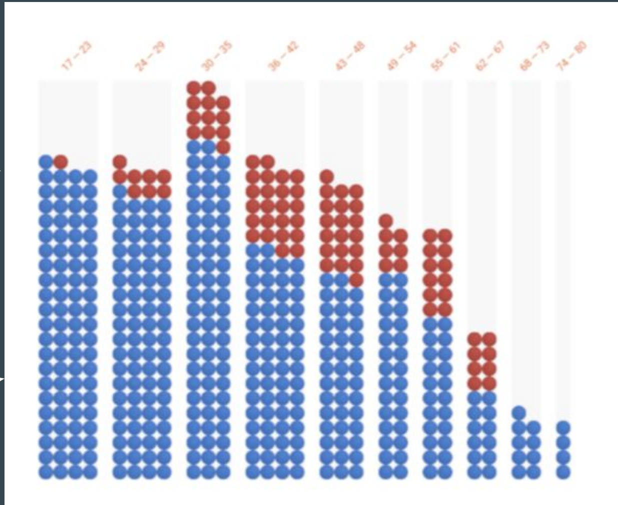
https://pair-code.github.io/what-if-tool/iris.html

What? - The Tool

Data

Machine Learning Model

What-If Tool



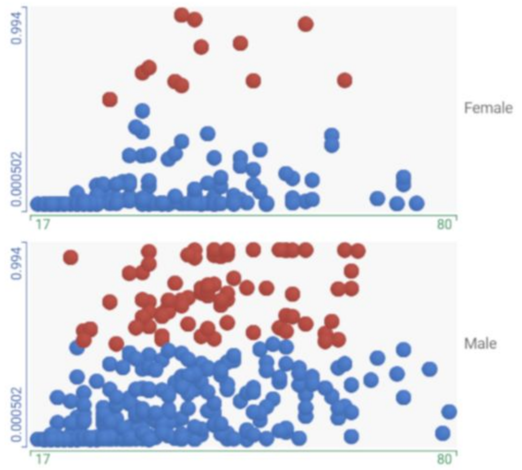
(b) Histogram of age, colored by classification

What? - The Tool

Data

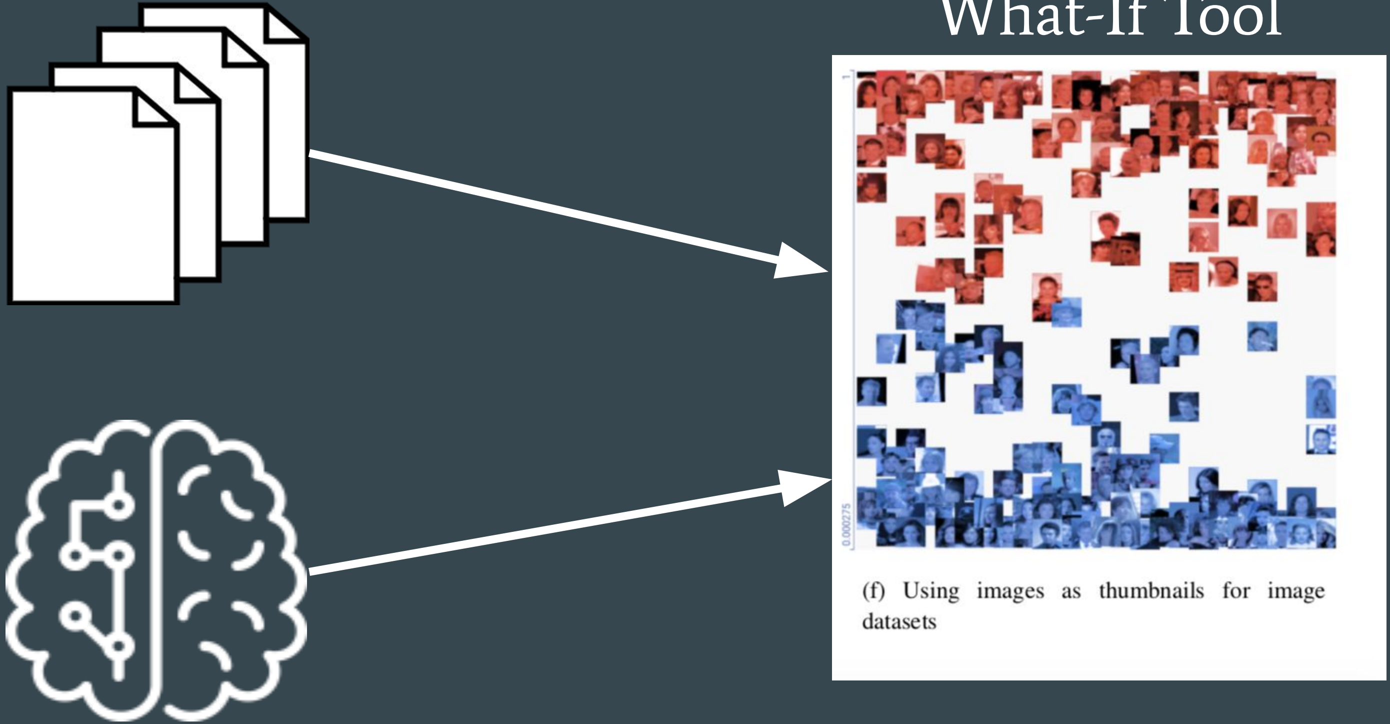
Machine Learning Model

What-If Tool



(d) Small multiples by sex. Each scatterplot shows age vs positive classification score, colored by classification

What? - The Tool

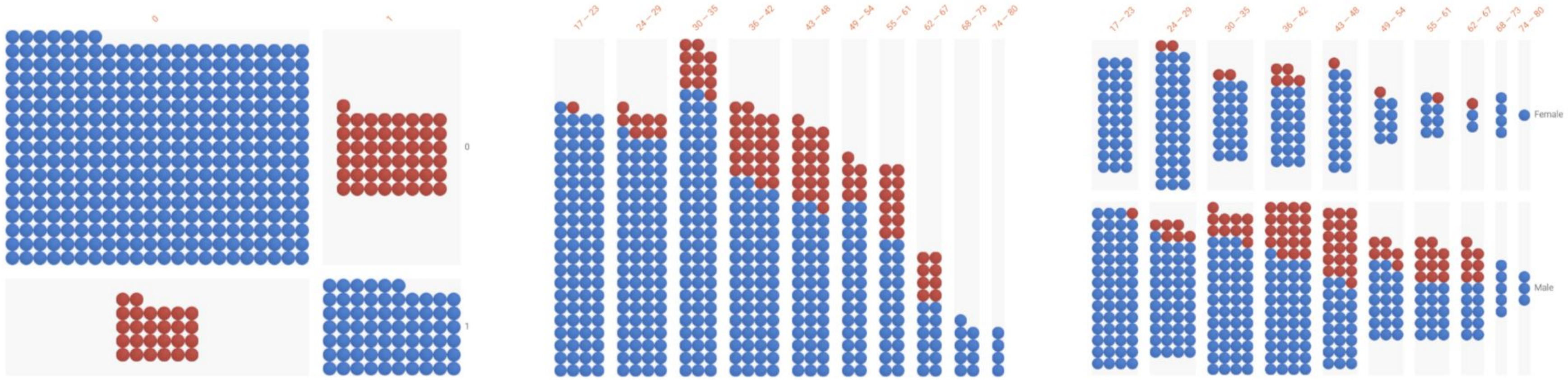


How? - Tailoring 3 Tasks to Satisfy User Needs

- Closely related to user needs
- Example of the UCI Census dataset
    - Solve prediction task
    - Classify individuals as high or low income
    - Train 2 models
        - Multi-layer neural network
        - Simple linear classifier

How? - Task 1: Exploring the Data

Customizable Analysis



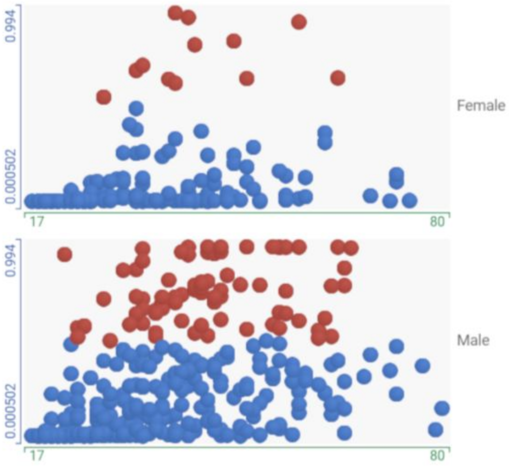
(a) Confusion matrix of a single binary classification model, colored by prediction correctness

(b) Histogram of age, colored by classification

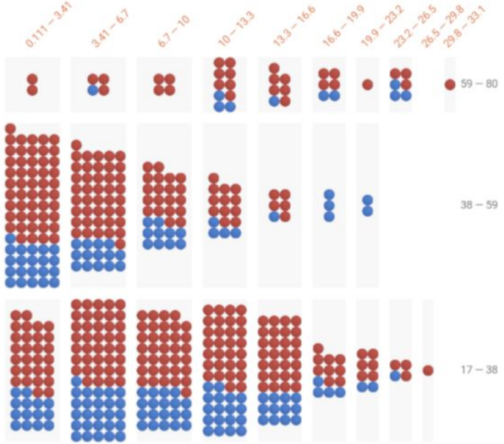
(c) Two-dimensional histogram of age and sex, colored by classification

How? - Task 1: Exploring the Data

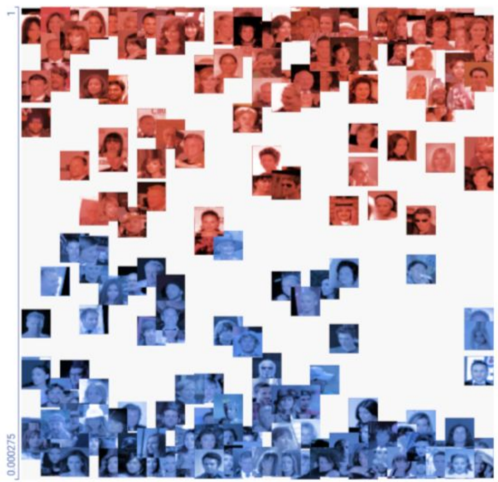
Customizable Analysis



(d) Small multiples by sex. Each scatterplot shows age vs positive classification score, colored by classification



(e) Histograms of performance in a regression model that predicts age, faceted into 3 age buckets



(f) Using images as thumbnails for image datasets

How? - Task 1: Exploring the Data

Feature Analysis: Dataset Summary

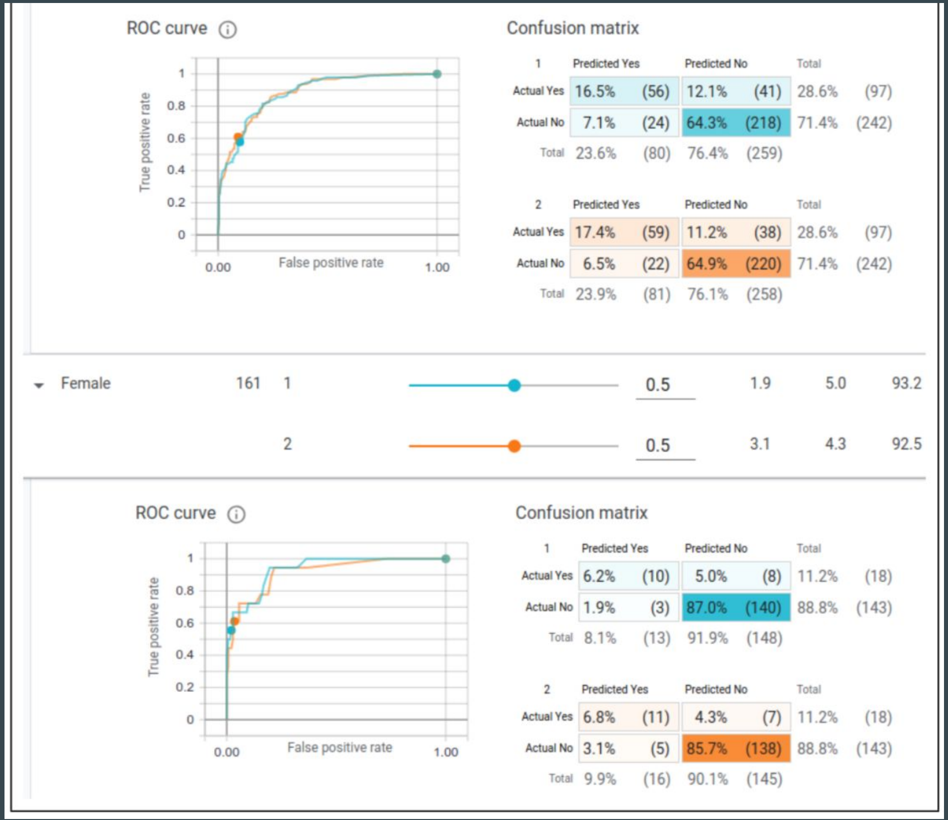
How? - Task 2: Investigating What-If Hypothesis

- Generate & test hypotheses about how model treats data
  - Edit data points
  - Identify counterfactuals
  - Observe partial dependencies
- Apply carefully chosen input modifications (edit, add or delete feature values)
- Result of changing income from \$3,000 → \$20,000 (edit data point):

Run	Model	Label	Score	Delta
2	1	1 (>50k)	0.991	↑ 0.655581
2	1	0 (<=50k)	0.008	↓ -0.641580
2	2	1 (>50k)	0.894	↑ 0.140262
2	2	0 (<=50k)	0.067	↓ -0.156162
1	1	0 (<=50k)	0.650	
1	1	1 (>50k)	0.336	

How? - Task 3: Evaluate Performance and Fairness

- Slice data by feature values
- Perform measures on the subset
  - ROC
  - Confusion Matrix
  - Cost Ratio
- Measures can also be applied to Compare models



Data Scaling

- Assumption: Standard laptop
- Computational restrictions:
  - Tabular Data:
    - # Features: 10-100
    - # Datapoints: ~100,000
  - Image Data:
    - Pixel dimensions: 78x64
    - # Datapoints: 2,000
- **Comment:**
  - **As seen before, occlusion already a problem with less data**

Evaluation

- 3 case studies executed
  - 2 studies in a large software company
  - 1 study in a university environment
- Showing the potential of WIT to:
  - Uncover bugs
  - Explore the data
  - Find partial dependencies

Analysis Summary

- **What data:**
  - User data & machine learning models
- **What derived:**
  - Inference of the model (on the data)
- **What shown:**
  - Dataset- and datapoint-level results of ML models
  - Giving a better understanding of the capabilities and possible adversarial attacks

Analysis Summary

- **How executed:**
    - 3 common tasks derived from user studies
- **How shown:**
    - Extension of a out-of-the-box visualization tool
- **Why important:**
    - Machine Learning models are black boxes
    - Making crucial decisions in the real world
    - Understanding is important

Strength and Weaknesses

Strengths:

+ Versatile tool
+ Many useful real-world applications
+ Greatly reducing workload compared to creating own visualizations

Weaknesses:

- Only easily compatible with Tensorflow (one deep-learning library)
- Occlusion is a problem, already with small datasets (150 data points, see example)
- Strict computational restriction (100,000 data points is not a lot)

Thank You

Questions?