Interpretability of ML Systems

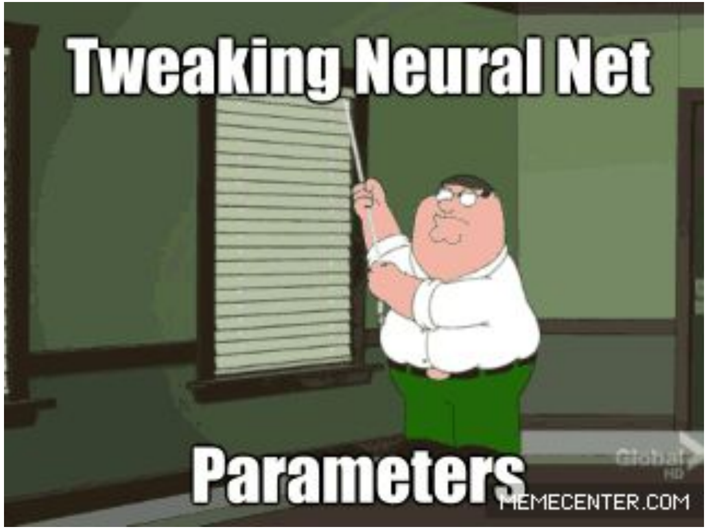
Philipp @ DSR

Class Outline

- Day 1
  - Introduction to Interpretability
  - Interpretability
    - Models
    - Notebooks/Exercises
  - Case study for vision/text based models

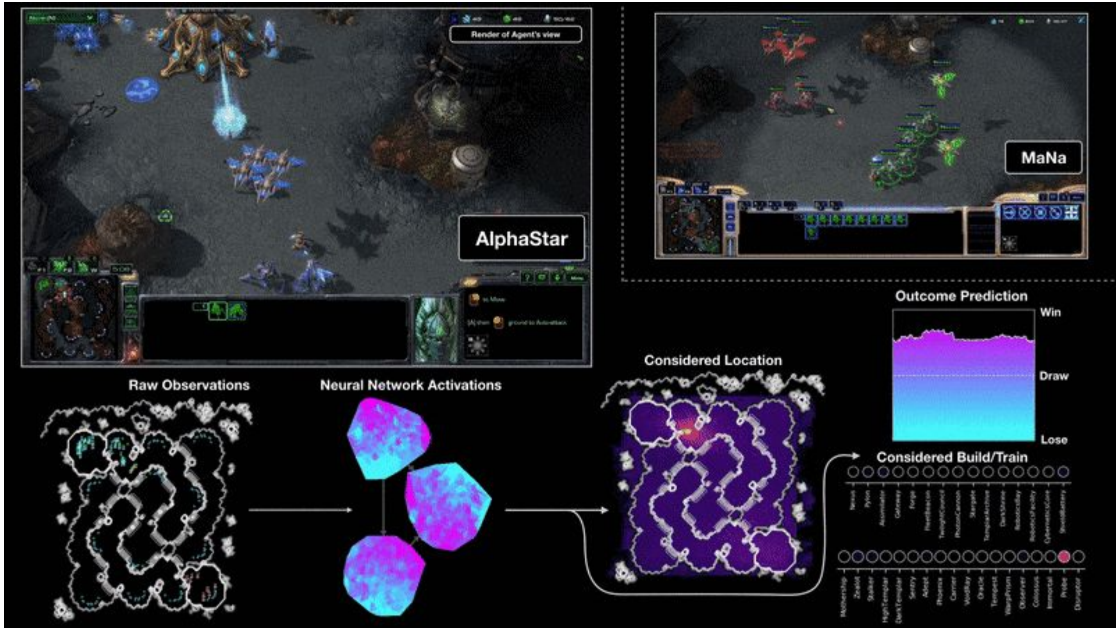
Some recent ML achievements

- DeepMind
  - AlphaZero
    - Chess/Go/Shogi
  - [WaveNet]
    - Generative model for raw Audio
    - Speech/Music



Some recent ML achievements

- DeepMind
  - AlphaStar: Beats competitive Starcraft II players



Some recent ML achievements

- OpenAI
  - Generative Language models
    - Machine translation
    - Question answering

SYSTEM PROMPT (HUMAN-WRITTEN)	*A train carriage containing controlled nuclear materials was stolen in Cincinnati today. Its whereabouts are unknown.*
MODEL COMPLETION (MACHINE-WRITTEN, FIRST TRY)	The incident occurred on the downtown train line, which runs from Covington and Ashland stations. In an email to Ohio news outlets, the U.S. Department of Energy said it is working with the Federal Railroad Administration to find the thief. “The theft of this nuclear material will have significant negative consequences on public and environmental health, our workforce and the economy of our nation,” said Tom Hicks, the U.S. Energy Secretary, in a statement. “Our top priority is to secure the theft and ensure it doesn’t happen again.”

Hang on

- All of these results are impressive
  - Scalability of training/prediction
  - Benchmarking in real-world settings
  - Massive models, massive data-sets

- Do we have enough tools to understand these models?

Why do we need to understand models?

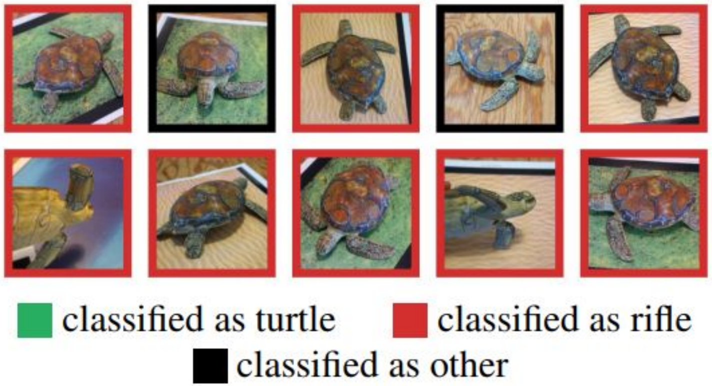


Figure 1. Randomly sampled poses of a 3D-printed turtle adversarially perturbed to classify as a rifle at every viewpoint[2]. An unperturbed model is classified correctly as a turtle nearly 100% of the time.

Athalye et al.
Synthesizing Robust Adversarial Examples
ICML 2018

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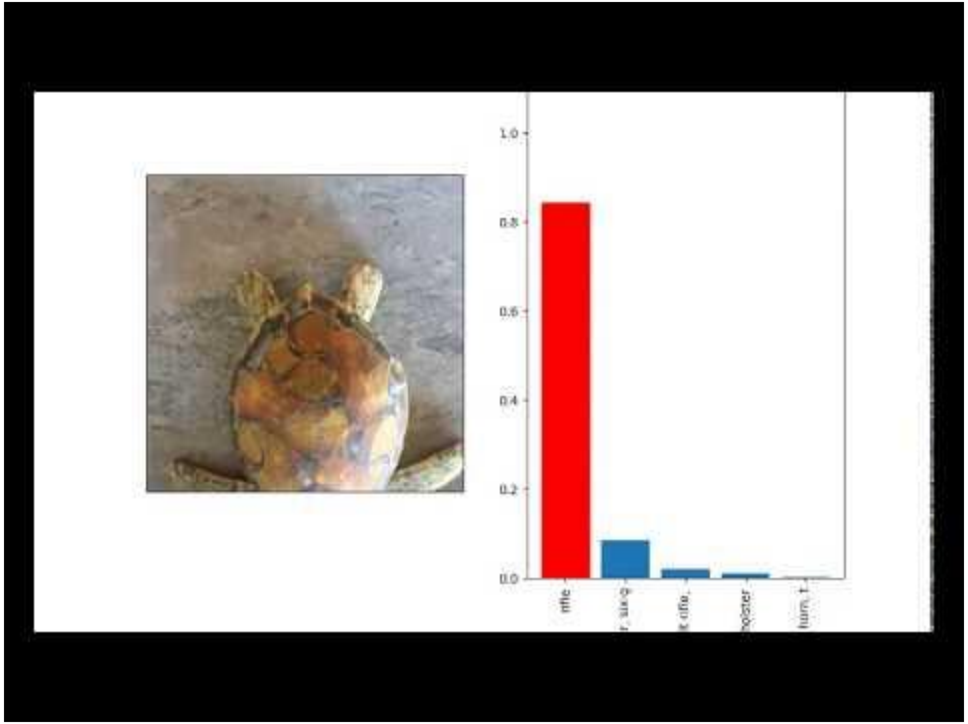

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Why do we need to understand models?

- Rise of ML-based systems
  - Complex, possibly interdependent black-boxes

Some ML models

- OpenAI's language model GPT-2 contains ~1.5 billion parameters

Model	Size	Top-1 Accuracy	Top-5 Accuracy	Parameters	Depth
Xception	88 MB	0.790	0.945	22,910,480	126
VGG16	528 MB	0.713	0.901	138,357,544	23
VGG19	549 MB	0.713	0.900	143,667,240	26
ResNet50	98 MB	0.749	0.921	25,636,712	-
ResNet101	171 MB	0.764	0.928	44,707,176	-
ResNet152	232 MB	0.766	0.931	60,419,944	-
ResNet50V2	98 MB	0.760	0.930	25,613,800	-
ResNet101V2	171 MB	0.772	0.938	44,675,560	-
ResNet152V2	232 MB	0.780	0.942	60,380,648	-
ResNeXt50	96 MB	0.777	0.938	25,097,128	-
ResNeXt101	170 MB	0.787	0.943	44,315,560	-
InceptionV3	92 MB	0.779	0.937	23,851,784	159
InceptionResNetV2	215 MB	0.803	0.953	55,873,736	572
MobileNet	16 MB	0.704	0.895	4,253,864	88
MobileNetV2	14 MB	0.713	0.901	3,538,984	88
DenseNet121	33 MB	0.750	0.923	8,062,504	121
DenseNet169	57 MB	0.762	0.932	14,307,880	169
DenseNet201	80 MB	0.773	0.936	20,242,984	201
NASNetMobile	23 MB	0.744	0.919	5,326,716	-
NASNetLarge	343 MB	0.825	0.960	88,949,818	-

The top-1 and top-5 accuracy refers to the model's performance on the ImageNet validation dataset.

Depth refers to the topological depth of the network. This includes activation layers, batch normalization layers etc.

https://keras.io/applications

Why do we need to understand models?

- Rise of ML-based systems
    - Complex, possibly interdependent black-boxes
- GDPR
    - In effect since 05/2018 in EU
    - “Meaningful explanations of the logic involved” for automated decision systems

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  - Complex, possibly interdependent black-boxes
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- Applications
  - (Social) credit scoring
  - Health
  - Safety

Social Credit System (China)

- Government owned assessment of economic and social reputation of chinese citizens

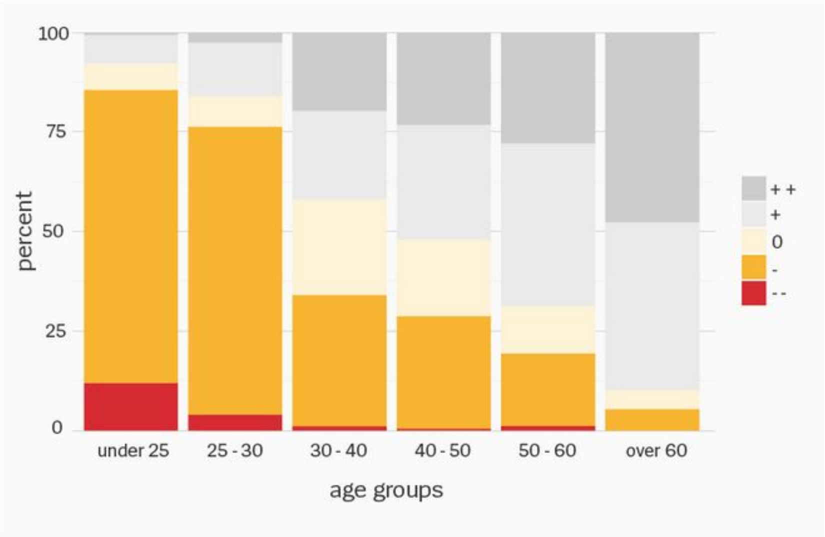
- Chinese courts banned people from buying Airplane and Train tickets more than 20 million times in 2018

Credit Scoring in Germany

- OpenSchufa
  - An initiative to reverse engineer scoring algorithm

- Schufa declared a trade secret by the Federal Court of Justice

Younger men more often have bad ratings than older ones

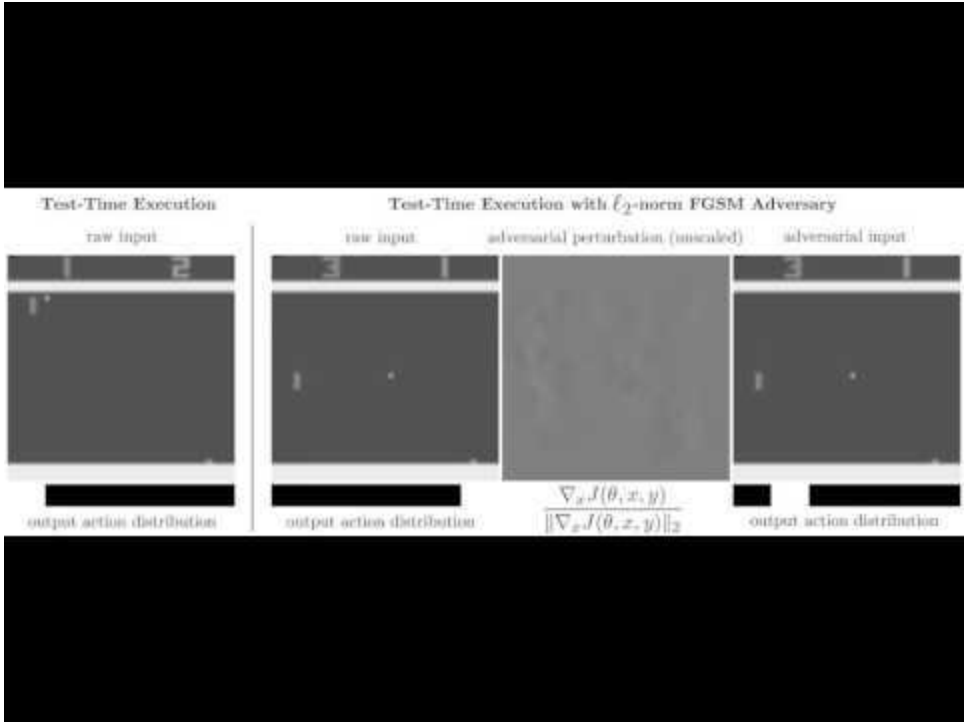


Classifications in the category „General Data" across different age groups.
Population: all male consumers in the dataset with less than three relocations.

https://web.br.de/interaktiv/erhoehtes-risiko/english/index.html

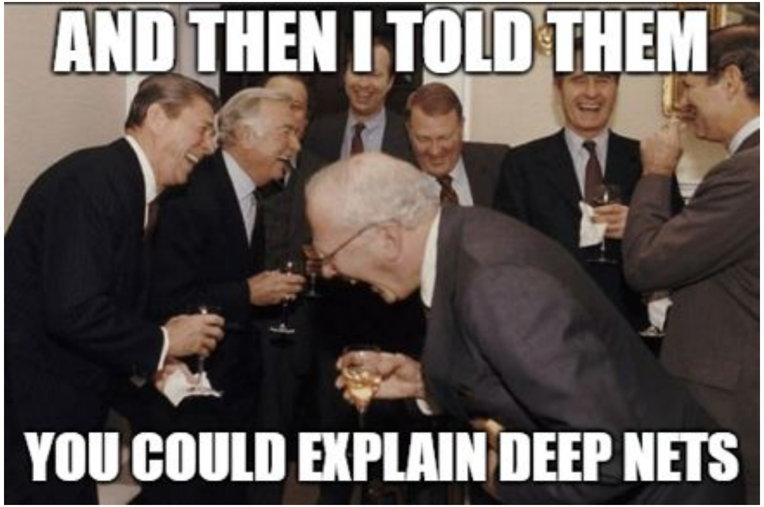
Safety

- Adversarial Attack
  on Deep Q-Network



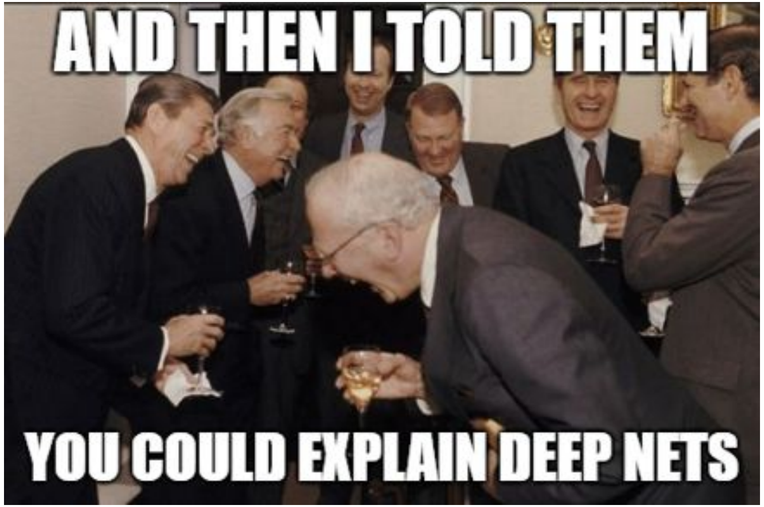
Huang, Sandy et al.
Adversarial Attacks on Neural Network Policies
arXiv preprint arXiv:1702.02284 (2017)

ML what?



ML what?

- Lots of active research is focussing on understanding and interpreting ML models
- How to define Interpretability?



Interpretability Desiderata

- Trust
  - In model performance
  - …
  - Drop human from the loop?

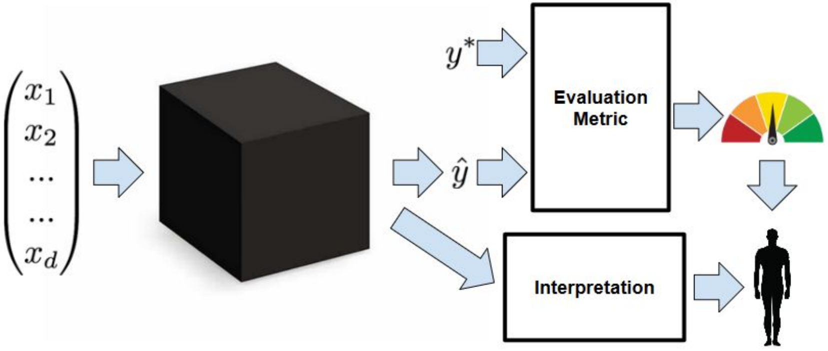


Figure 1. Typically, evaluation metrics require only predictions and *ground truth* labels. When stakeholders additionally demand *interpretability*, we might infer the existence of desiderata that cannot be captured in this fashion.

Lipton
The mythos of model interpretability
arXiv preprint arXiv:1606.03490 (2016)

Interpretability Desiderata

- Causality
  - Models learned mostly from observational data

TABLE 4.1: The results of fitting a logistic regression model on the cervical cancer dataset. Shown are the features used in the model, their estimated weights and corresponding odds ratios, and the standard errors of the estimated weights.

	Weight	Odds ratio	Std. Error
Intercept	2.91	18.36	0.32
Hormonal contraceptives y/n	0.12	1.12	0.30
Smokes y/n	-0.26	0.77	0.37
Num. of pregnancies	-0.04	0.96	0.10
Num. of diagnosed STDs	-0.82	0.44	0.33
Intrauterine device y/n	-0.62	0.54	0.40

Interpretation of a numerical feature ("Num. of diagnosed STDs"): An increase in the number of diagnosed STDs (sexually transmitted diseases) changes (decreases) the odds of cancer vs. no cancer by a factor of 0.44, when all other features remain the same. Keep in mind that correlation does not imply causation. No recommendation here to get STDs.

Molnar
Interpretable Machine Learning
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Interpretability Desiderata

- Fairness
  - Is the model fair?

- Can fairness be measured objectively?
  - Dozens of metrics for fairness in social sciences and statistics

Interpretability Desiderata

- What do you think?

Getting Started

- Clone GitHub repo
  - **git clone git@github.com:tdhd/interpretability-class.git**
- Setup local environment
- Prepared notebooks in
  - https://github.com/tdhd/interpretability-class/tree/master/exercises

- Questions?

Linear regression

- One of the most studied models in Statistics

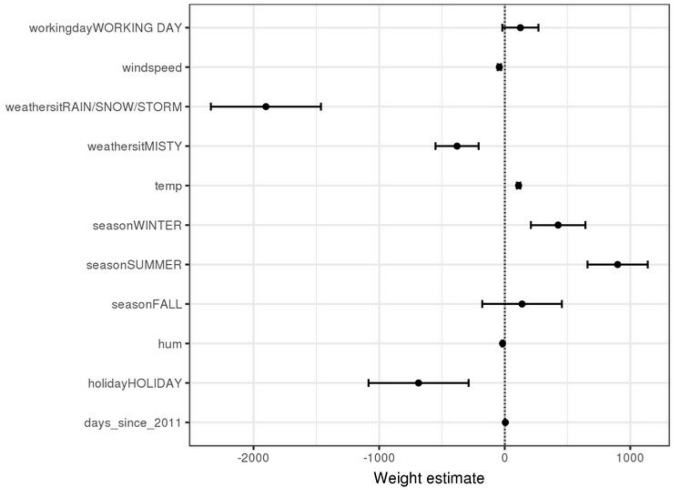

FIGURE 4.1: Weights are displayed as points and the 95% confidence intervals as lines.

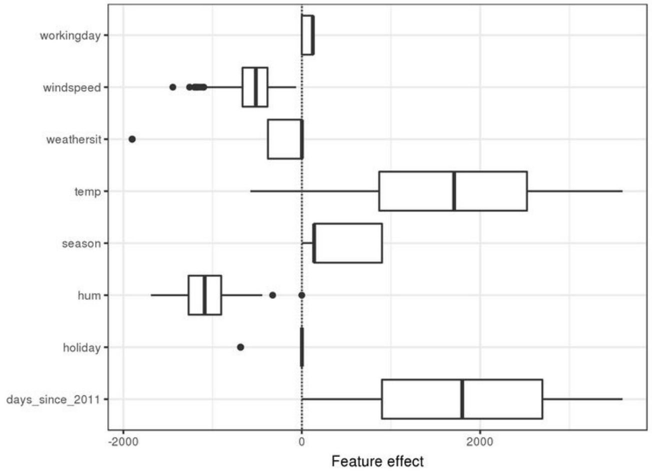

FIGURE 4.2: The feature effect plot shows the distribution of effects (= feature value times feature weight) across the data per feature.

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Interpretable Machine Learning
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Logistic Regression

- Popular baseline for classification tasks
- Weights have non-linear influence on outcome

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Decision Trees

- Decision trees usually constructed top-down
  - Greedy selection of variable according to most reduces a metric
  - Regression metric: Variance Reduction
  - Classification metrics: Gini impurity / Information Gain
- Explaining a Decision Tree
  - Tree decomposition
    - Follow path through tree for single instance
  - Feature importance
    - Measure change in Information Gain / variance

Interpretation of weight vectors

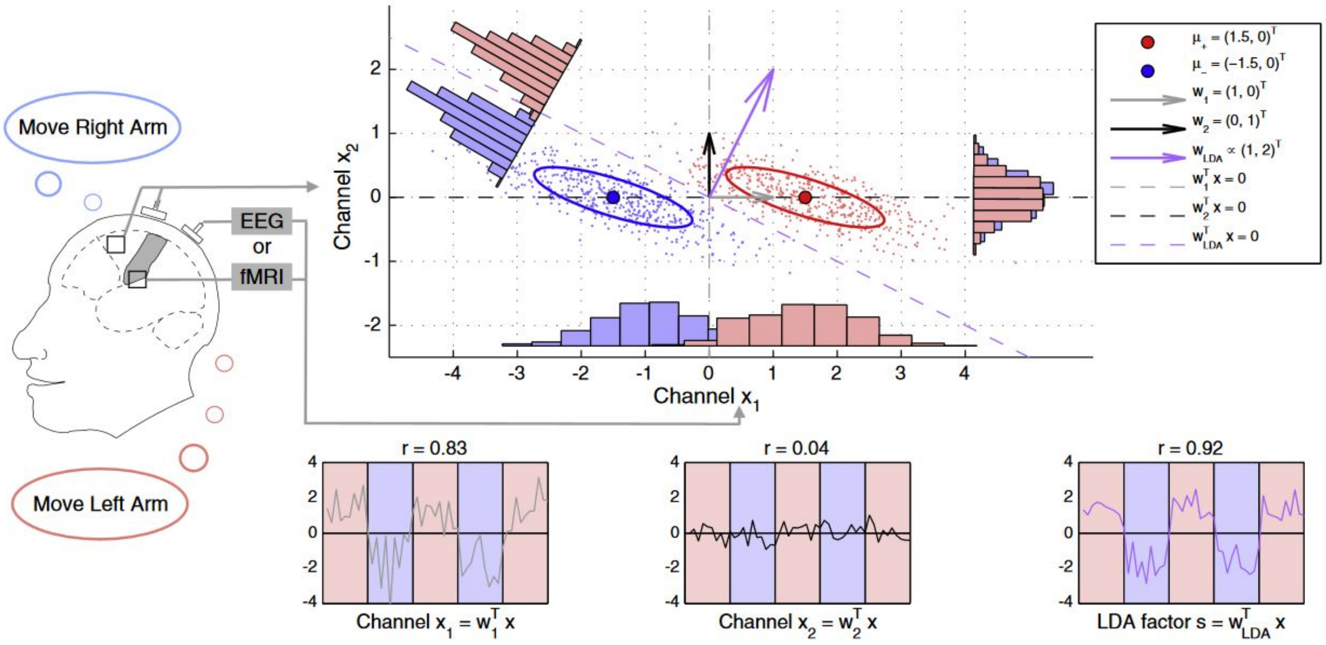
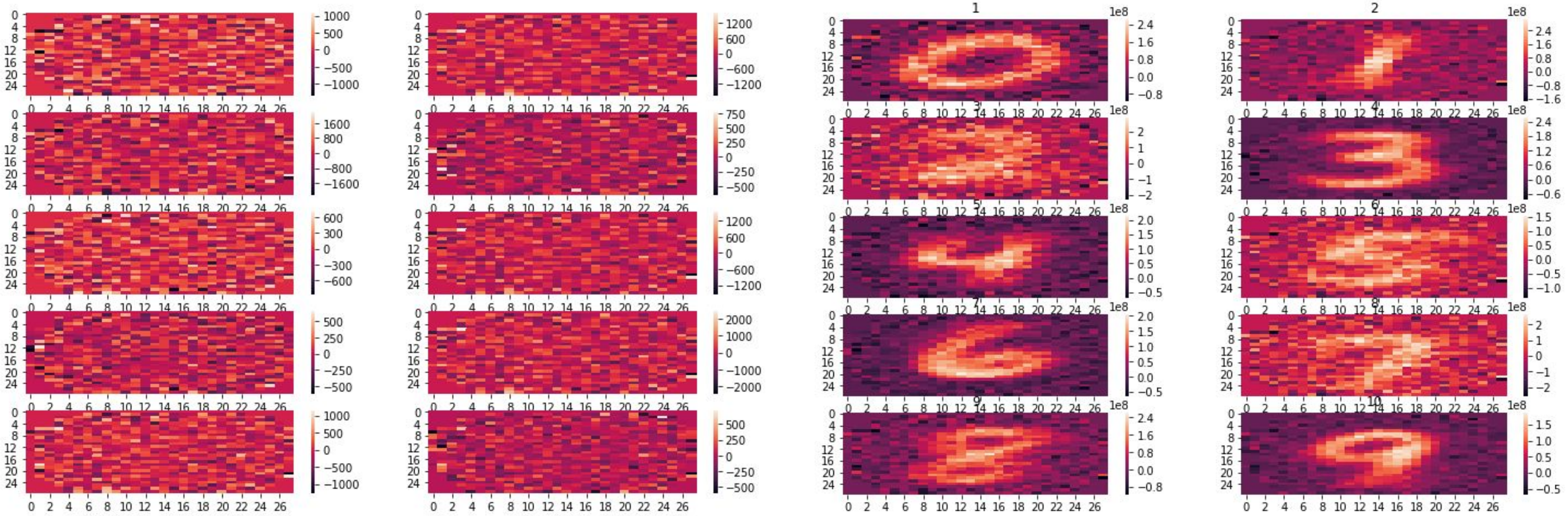


Fig. 1. Two-dimensional example of a binary classification setting. The class-conditional distributions are multivariate Gaussians with equal covariance matrix. The class means differ in channel $x_1(n)$, but not in channel $x_2(n)$. Thus, channel $x_2(n)$ does not contain any class-related information. Nevertheless, Bayes-optimal classification according to linear discriminant analysis (LDA) projects the data onto the weight vector (extraction filter) $\mathbf{w}_{\text{LDA}} \propto [1, 2]^{\text{T}}$, i.e., assigns twice the weight of channel $x_1(n)$ to channel $x_2(n)$. This large weight on $x_2(n)$ is needed for compensating the skewed correlation structure of the data, and must not be interpreted in the sense that the activity at $x_2(n)$ is class-specific. By transforming the LDA projection vector into a corresponding activation pattern $\mathbf{a}_{\text{LDA}}$ using Eq. (7), we obtain $\mathbf{a}_{\text{LDA}} \propto [1, 0]^{\rightarrow P}$, which correctly indicates that $x_1(n)$ is class-specific, while $x_2(n)$ is not.

Haufe et al.
[On the interpretation of weight vectors of linear models in multivariate neuroimaging]
NeuroImage, 2013

Comparison: weights vs. patterns



Class patterns

- Computes class-patterns
  - Given label estimates Y with k classes and d features
  - Compute pattern matrix A with d rows and k columns
    - A = Cov(X, Y) = X.T @ X @ W
  - Column i of A corresponds to the pattern of class i
- Above computation for uncorrelated label estimates

LIME

- How does it work?
    - Select instance of interest for which you want to have an explanation
    - Perturb your dataset and get the black box predictions for these new points
    - Weight the new samples according to their proximity to the instance of interest
    - Train a weighted, interpretable model on the dataset with the variations
    - Explain the prediction by interpreting the local model
- Depending on input domain, pertubation different
    - Text: Randomly remove words
    - Images: Random remove super-pixels
- Authors provide python package, explains
    - Text
    - Images

LIME exercises

- Proposed approach
  - Pretrained models from https://keras.io/applications
- Explain different inputs
  - Sample notebook: github.com/marcotcr/lime