Explainable Machine Learning in Deployment

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Growth of Transparency Literature

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Many algorithms proposed to "explain" machine learning model output

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We study how organizations use these algorithms, if at all

Our Approach

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30 minute to 2 hour semi-structured interviews

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50 individuals from 30 organizations interviewed

Shared Language

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- **Transparency**: Providing stakeholders with relevant information about how a model works.
- Explainability: Providing insights into a model's behavior for specific datapoint(s)

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Example Questions

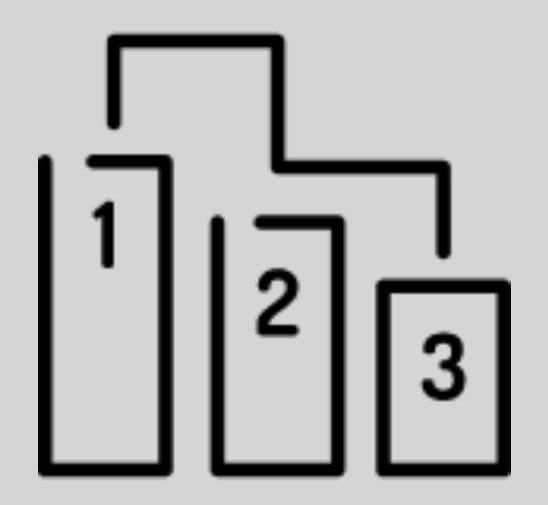
- What type of explanations have you used (e.g., feature-based, sample-based, counterfactual, or natural language)?
- Who is the audience for the model explanation (e.g., research scientists, product managers, domain experts, or users)?
- In what context have you deployed the explanations (e.g., informing the development process, informing human decision makers about the model, or informing the end user on how actions were taken based on the model's output)?

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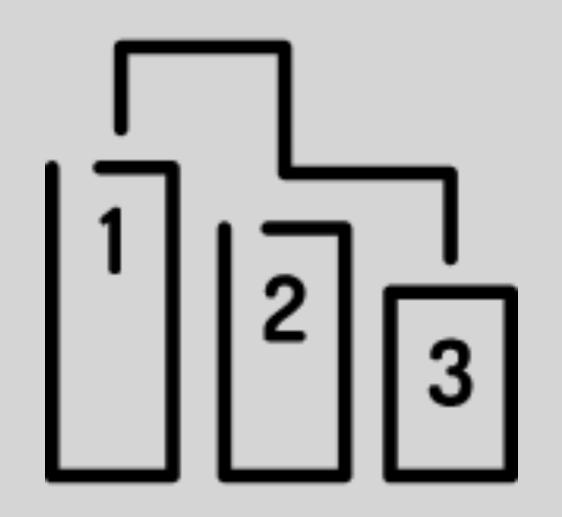
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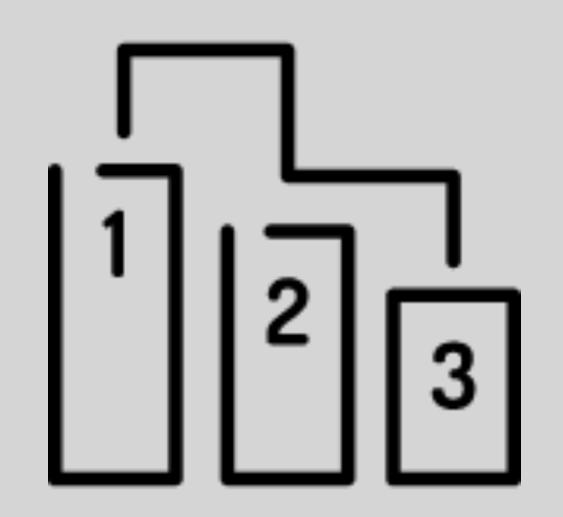
Feature Importance







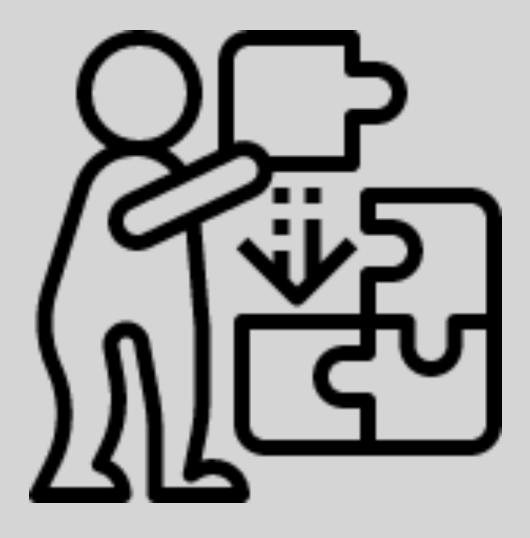
Sample Importance



Feature Importance



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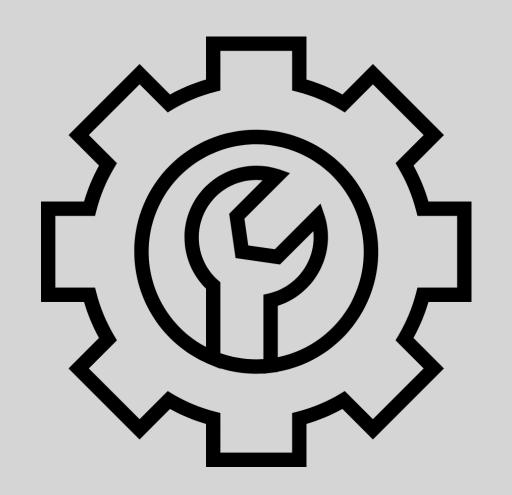


Counterfactuals



Executives

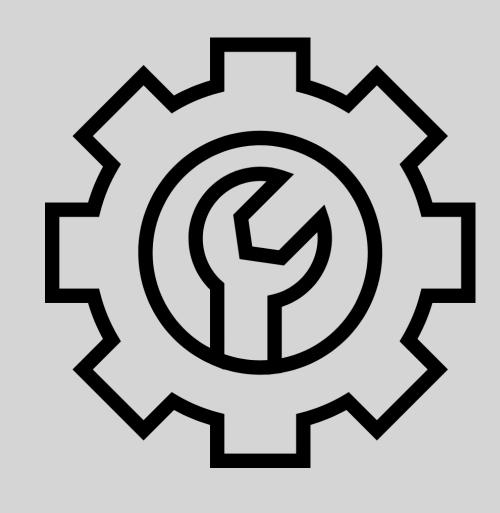




Executives

Engineers





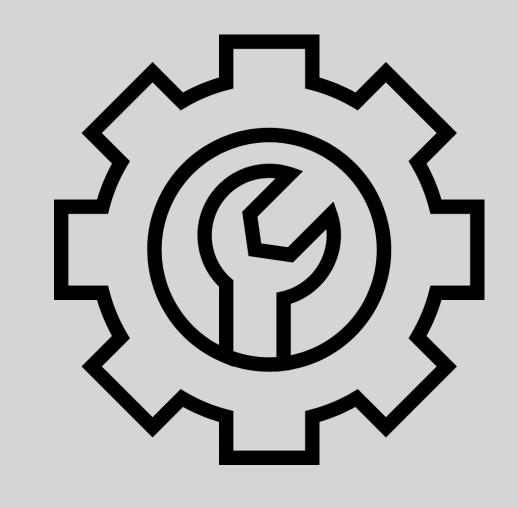


Executives

Engineers

End Users









Executives

Engineers

End Users

Regulators

Findings

- 1. Explainability used for debugging internally
- 2. Goals of explainability are not clearly defined within organizations
- 3. Technical **limitations** make explainability hard to deploy in real-time

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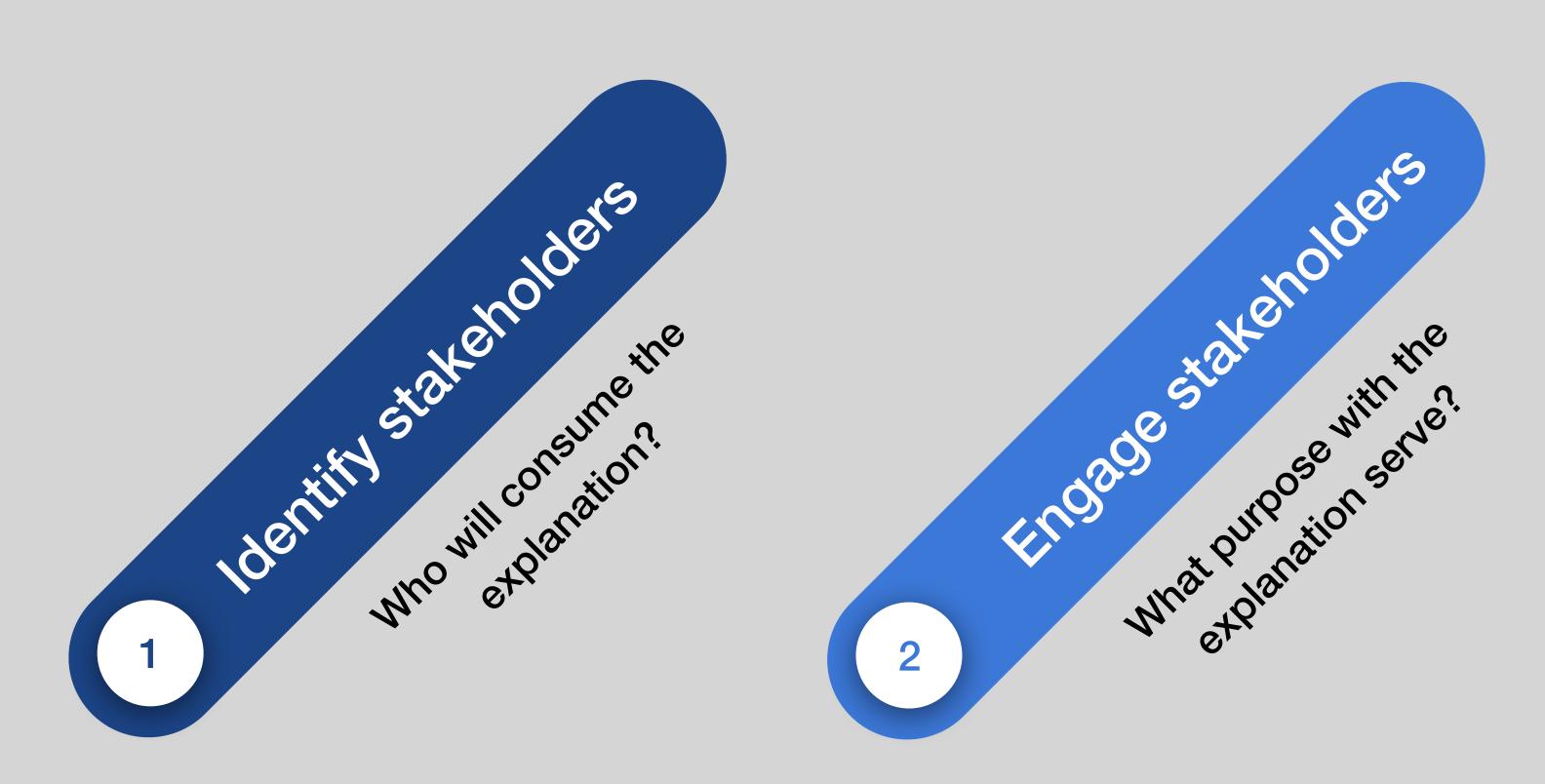
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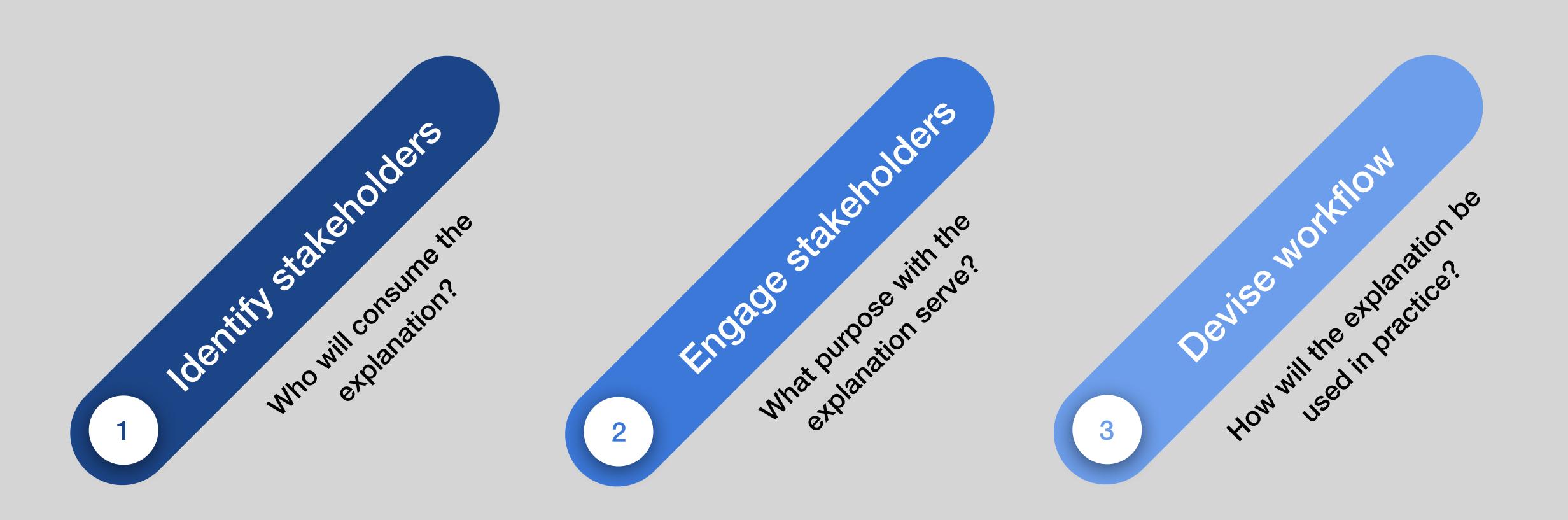
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Spurious correlations exposed by feature level explanations

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No causal underpinnings to the models themselves

 Sample importance is computationally infeasible to deploy at scale

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Privacy concerns of model inversion

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