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UNIVERSIDADE NOVA DE LISBOA

Concept-based Explainability:
Challenges & Applications to Fraud Detection

Vladimir Balayan, Catarina Belém, Pedro Saleiro, Ludwig Krippahl, Pedro Bizarro

Deep Learning Sessions Lisbon - Meetup
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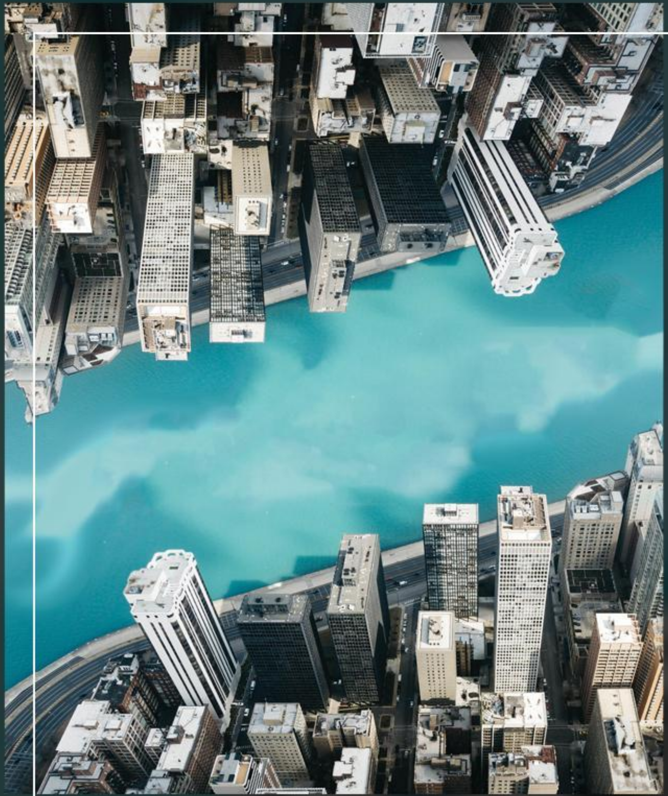

Problem & Motivation

Problem

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- The field of eXplainable AI (XAI) aims to tackle the lack of interpretability in ML.

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  1. produce low-level feature attributions explanations that are not suited for non-ML experts (e.g. fraud analyst).

Problem

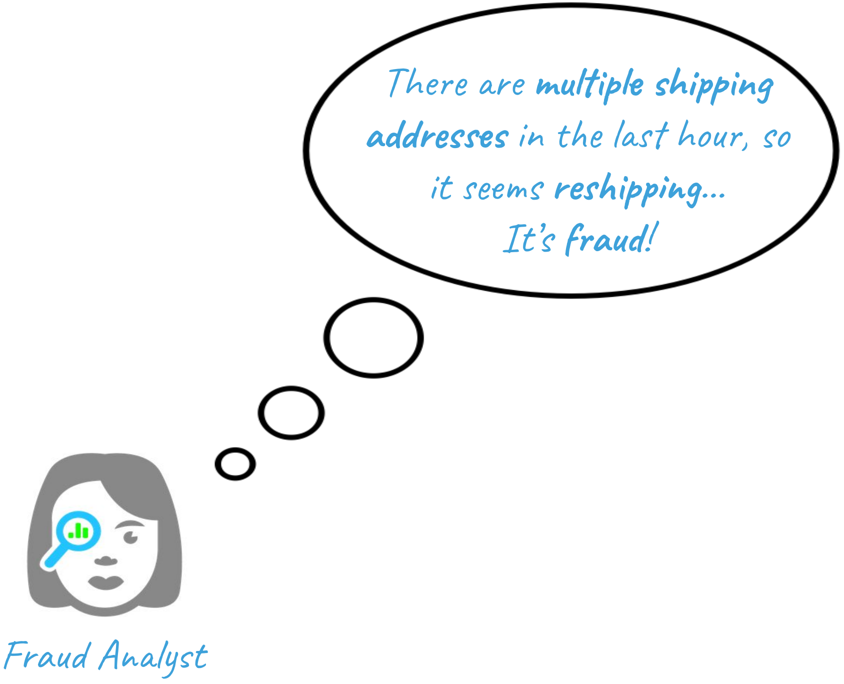
- The field of eXplainable AI (XAI) aims to tackle the lack of interpretability in ML.
- State-of-the-art methods in explainable AI (XAI) either:

  1. produce low-level feature attributions explanations that are not suited for non-ML experts (e.g. fraud analyst).

  Or

  2. produce concept-based explanations that do not work for tabular data.

Domain expert reasoning example



Domain expert reasoning example

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The ***ideal*** human-interpretable explanation for domain experts provide the ***high-level*** insights about the models' predictions.

Goals

- Develop a self-explainable neural network that jointly learn a predictive task and also associated domain knowledge explanations.

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- Develop a taxonomy of fraud concepts to be used as explanations.

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- Leverage the human-in-the-loop feedback to continuously improving both predictive accuracy and explainability.

Goals

- Develop a self-explainable neural network that jointly learn a predictive task and also associated domain knowledge explanations.
- Develop a taxonomy of fraud concepts to be used as explanations.
- Leverage the human-in-the-loop feedback to continuously improving both predictive accuracy and explainability.
- Create a semantic mapping bootstrapping strategy for automatically labeling concept-based explanations dataset.

Proposed solution in a real world fraud detection setting

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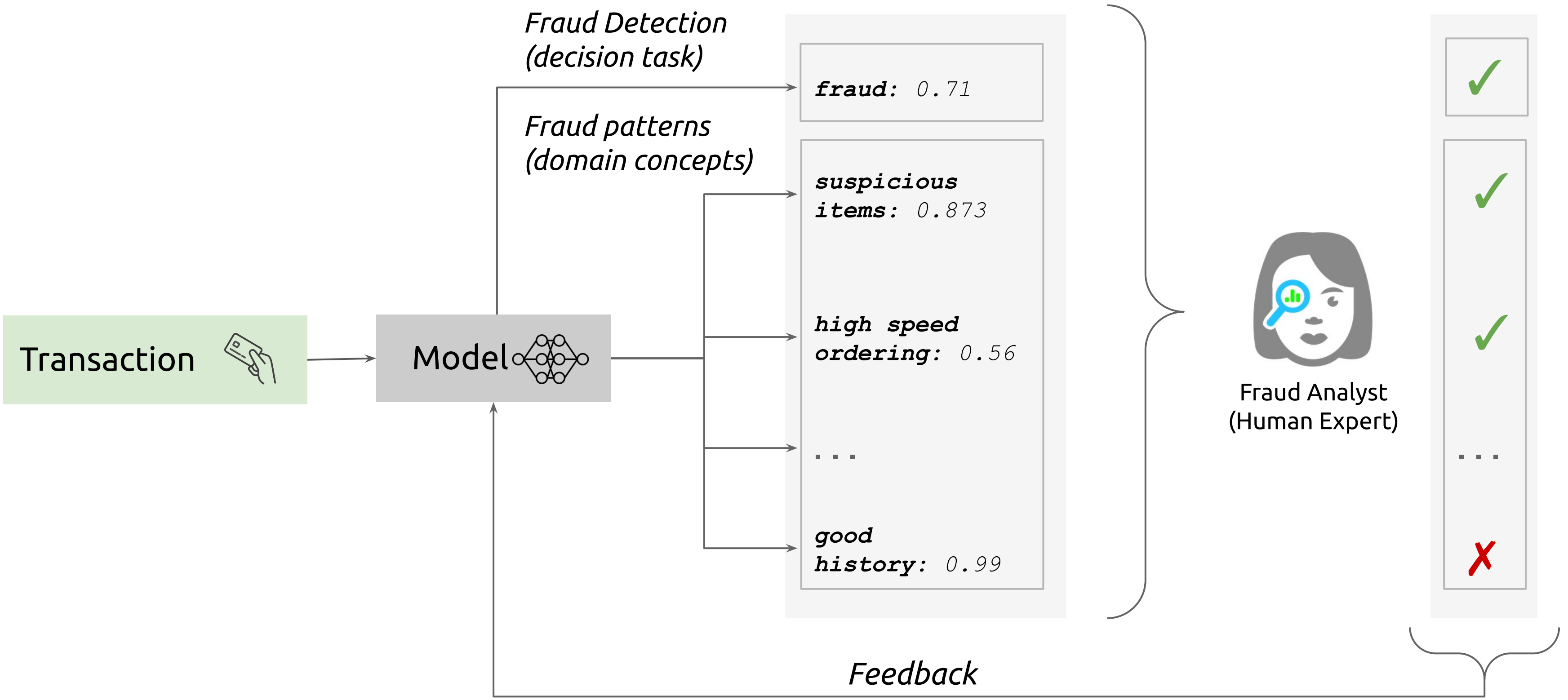

Background & Related Work

XAI Personas - Different personas, different XAI needs...

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Fields of expertise:

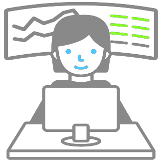
- Domain knowledge
- No ML knowledge

- Data Science + ML

- Know what they want
- No domain nor ML knowledge

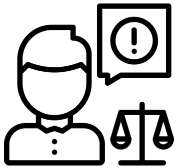
- Regulations/law
- Limited domain & ML knowledge

Human-in-the-loop



Data Scientist

Decision Subject



Regulator

Goals:

- Efficiency
- Better & faster decisions

- Efficiency
- Iterate and debug models

- Improve outcomes
- Reduce friction while feeling safe

- Audit and Assess
- if the system is compliant.

XAI Personas - Different personas, different XAI needs...

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Human-in-the-loop

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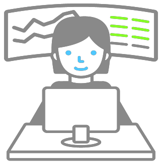

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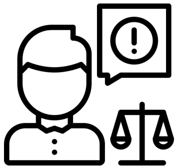

Regulator

- Regulations/law
- Limited domain & ML knowledge

- Audit and Assess
- if the system is compliant.

*The transaction is **suspicious** because MCC = 7801.*

*The transaction is **suspicious** because it contains Suspicious Items.*

XAI Personas - Different personas, different XAI needs...

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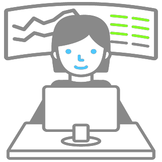
Human-in-the-loop



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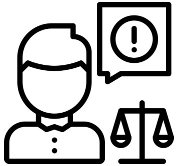

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Data Scientist
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Decision Subject
- Improve outcomes
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Regulator
- Audit and Assess
- if the system is compliant.

The optimal choice of explanation depends on the end persona!

Interpretability: When to build

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When to build?

- **Model-free**
  - EDA
- **In-model**
  - GAM (Lou 2012)
  - SENN (Alvarez-Melis 2019)
- **Post-hoc**
  - LIME (Ribeiro 2016)
  - DeepLIFT (Shrikumar 2017)
  - SHAP (Lundberg 2017)
  - LORE (Guidotti 2018)
  - Anchors (Ribeiro 2018)
  - Foil Trees (Waa 2018)

Interpretability: When to build

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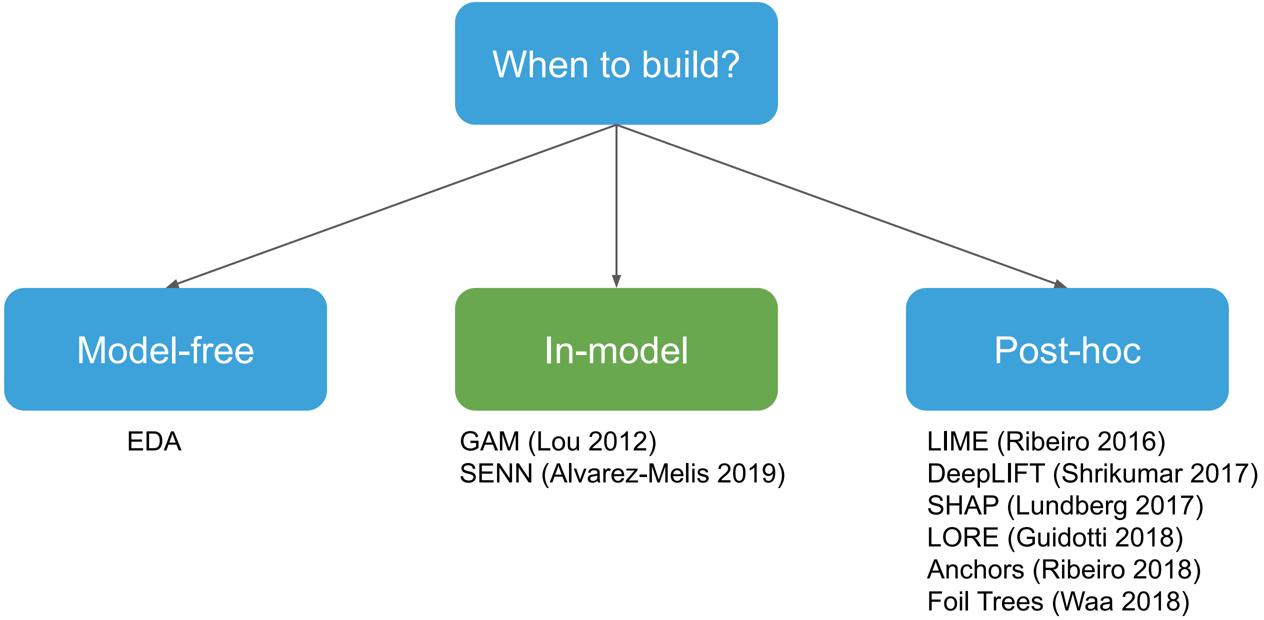

Taxonomy of Explanations’ Output

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Explanation output

- Feature-based
  (Greenwell 2017)
  (Ribeiro 2018)
  (Molnar 2019)
- Example-based
  (Dhurandhar 2018)
  (Plumb 2018)
  (Waa 2019)
- Model internals
  (Guo 2018)
- Concept-based
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There are many different methods and libraries available

Alibi

TreeInterpreter

DeepLift

LORE

TCAV

SHAP

DiCE

SENN

LIME

Attention

ACE

Anchors

Saliency

GradCAM

GuidedBackprop

Integrated Gradients

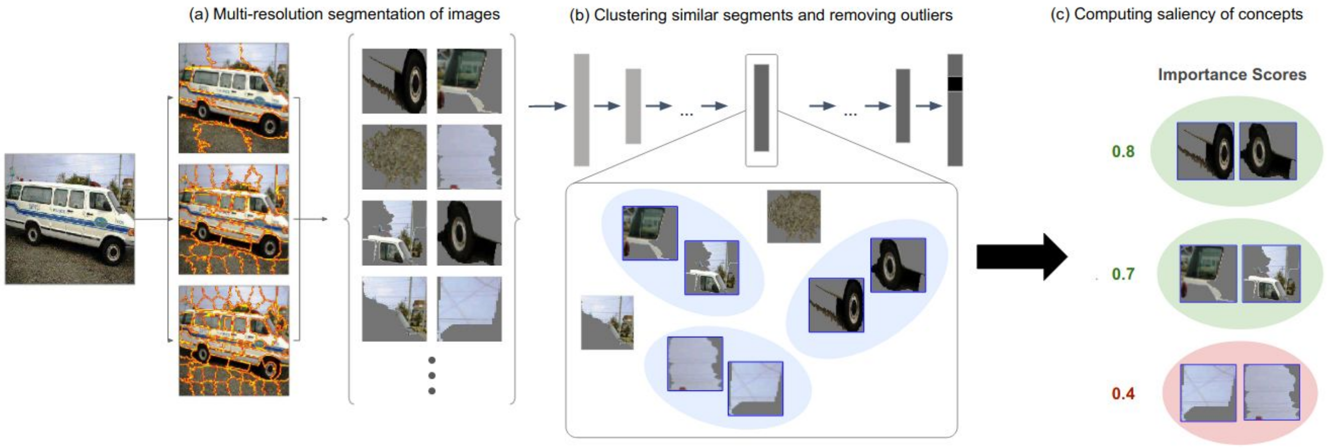
And others…

Automated Concept-based Explanation

Ghorbani, A, NeurIPS 2019, Towards Automatic Concept-based Explanations

- ACE is a global (and local), model-specific and concept-based explanation method that automatically groups input features into high-level concepts.

- The concepts are represented by groups of pixels (segments).



Our Explainability Requirements

To best to our knowledge, there is state-of-the-art XAI method that satisfies our explainability requirements.

In-Model

Local

Concept-based

Tabular data

Proposed Solution

Jointly learned cOncept-based ExpLanations (JOEL)

- JOEL, a NN-based framework to jointly learn a decision-making task and associated domain knowledge explanations.

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- JOEL is a self-explainable model, i.e., it incorporates the interpretability architecturally, allowing to produce the decision and also the explanations related to its decision.

Jointly learned cOncept-based ExpLanations (JOEL)

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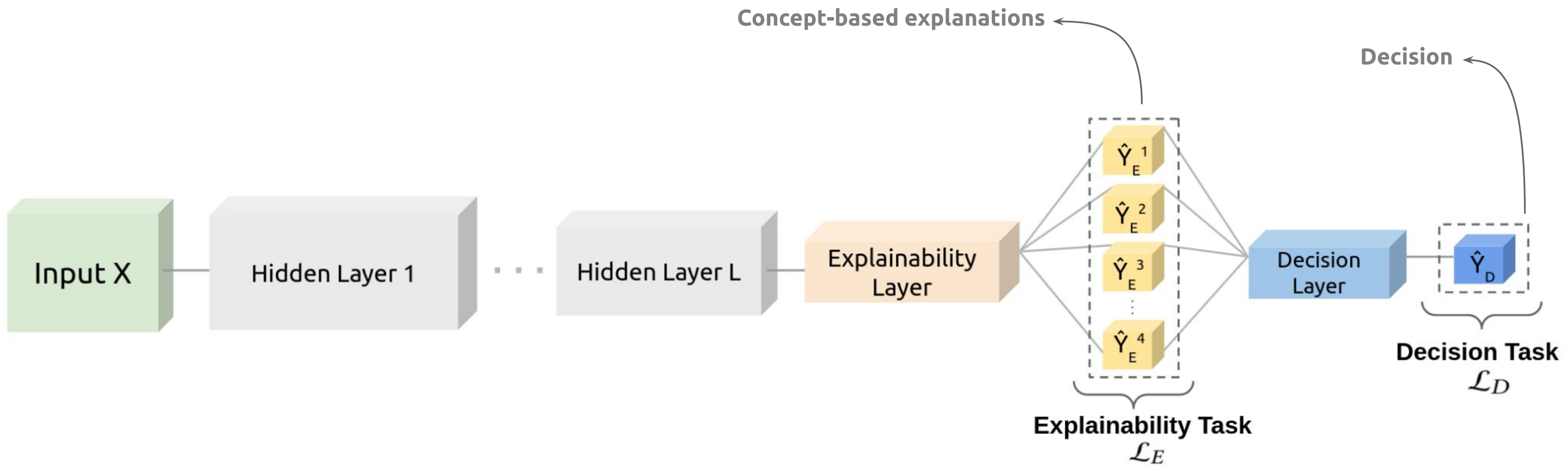
- JOEL, a NN-based framework to jointly learn a decision-making task and associated domain knowledge explanations.

- JOEL is a self-explainable model, i.e., it incorporates the interpretability architecturally, allowing to produce the decision and also the explanations related to its decision.

- JOEL provides high-level insights about the model's predictions that very much resemble the domain experts' own reasoning.

JOEL architecture



JOEL architecture

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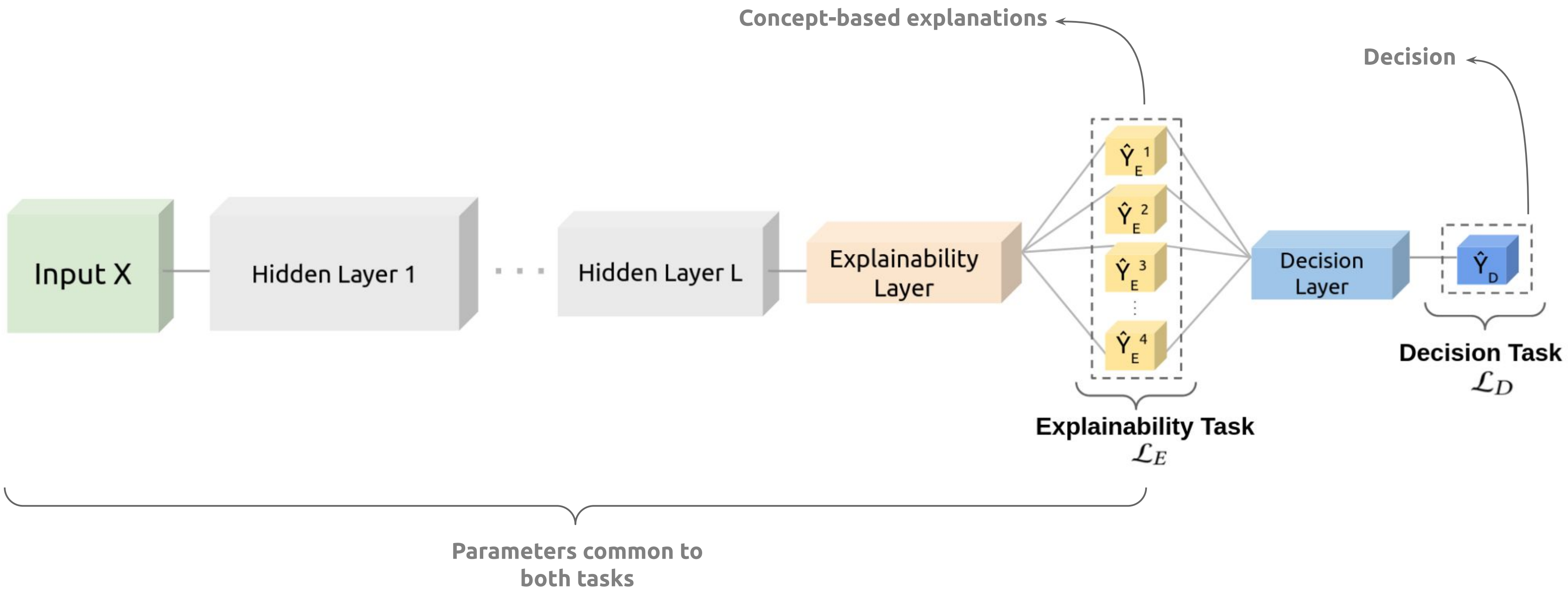

JOEL architecture

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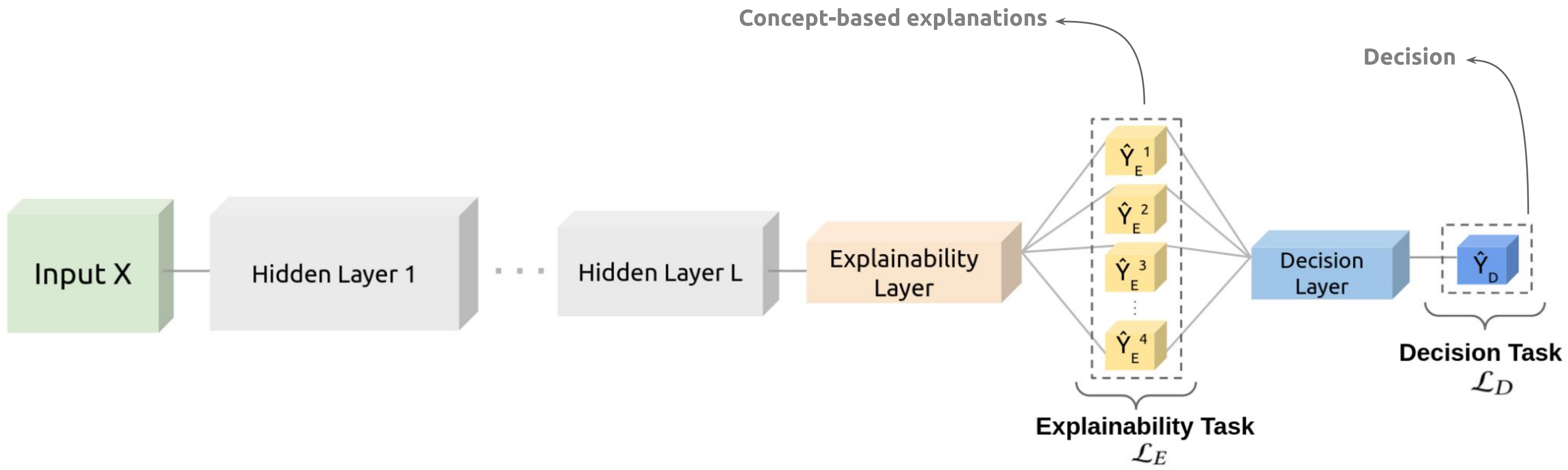

$$\mathcal{L}(\boldsymbol{x}, \boldsymbol{y}_E, \boldsymbol{y}_D) = \mathcal{L}_D(\hat{\boldsymbol{y}}_D, \boldsymbol{y}_D) + \mathcal{L}_E(\hat{\boldsymbol{y}}_E, \boldsymbol{y}_E)$$

Concept-Based Explainability and its limitations

Our problem is characterized by having:

- High-resources for the decision task **but** low-resources for the explainability task;
- Out-of-the-shelf domain knowledge (with no added cost).

Research Question:

*Can we **do better** than the **fully supervised** and **low-resources** baseline?*

Challenges

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Label Scarcity
(insufficient concept labels)

Multi-task Learning
(how to explain the model's predictions?)

- Good DL generalization requires massive datasets;
- Labeling campaigns are arduous and expensive to carry;

- Explainability task should explain the decision task;
- Explanations must reflect the human-in-the-loop's reasoning.

Possible solutions

1. Explore **Weak Supervision** techniques;
   - Can we leverage domain expertise and already existing components in Human-AI system?

Possible solutions

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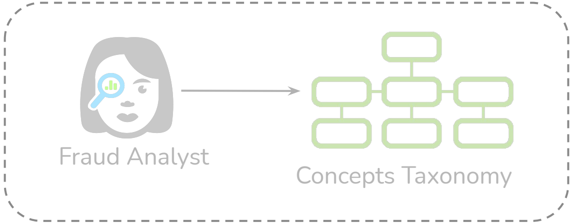
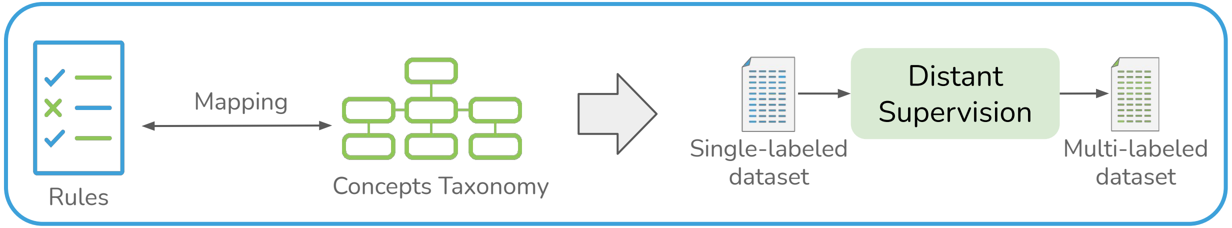
1. Explore **Weak Supervision** techniques;
   - Can we leverage domain expertise and already existing components in Human-AI system?

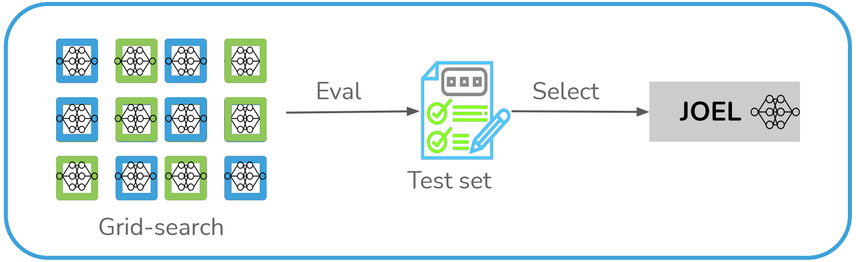
2. Explore different **Learning Strategies**;
   - Use noisy labels only?
   - Use noisy labels and then fine-tune using golden labels?
   - Mix both labels?

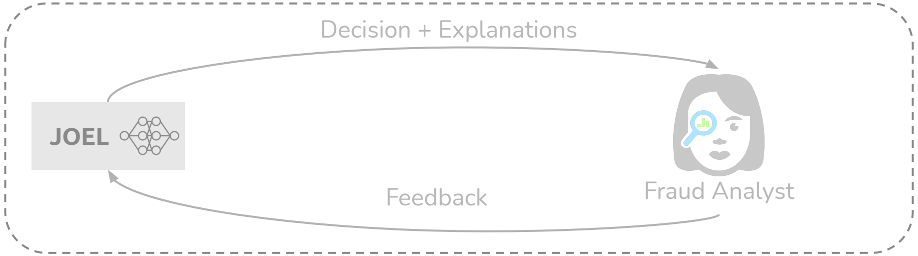
Implementation Workflow





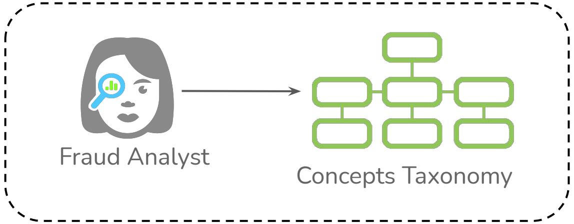
Label Scarcity





Multi-task learning

Implementation Workflow



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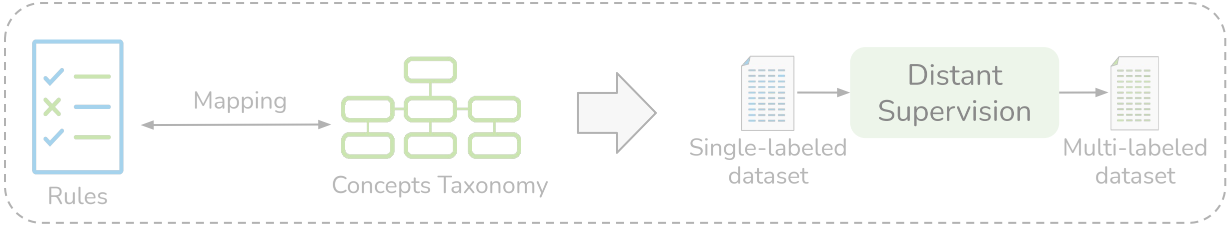
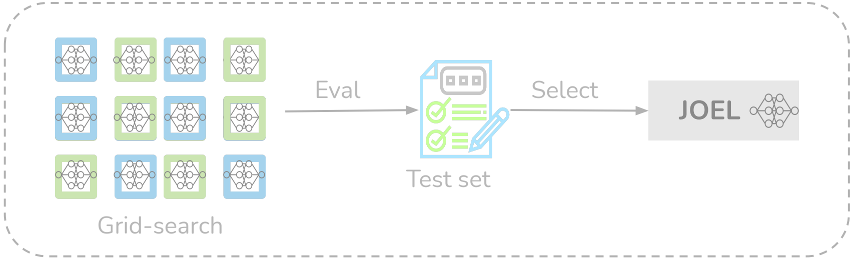
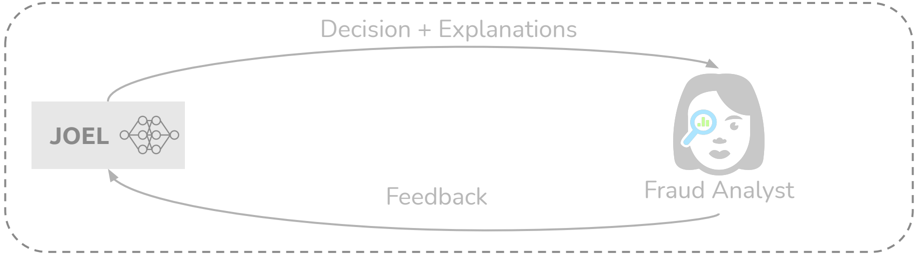


2 **Apply Distant Supervision.**

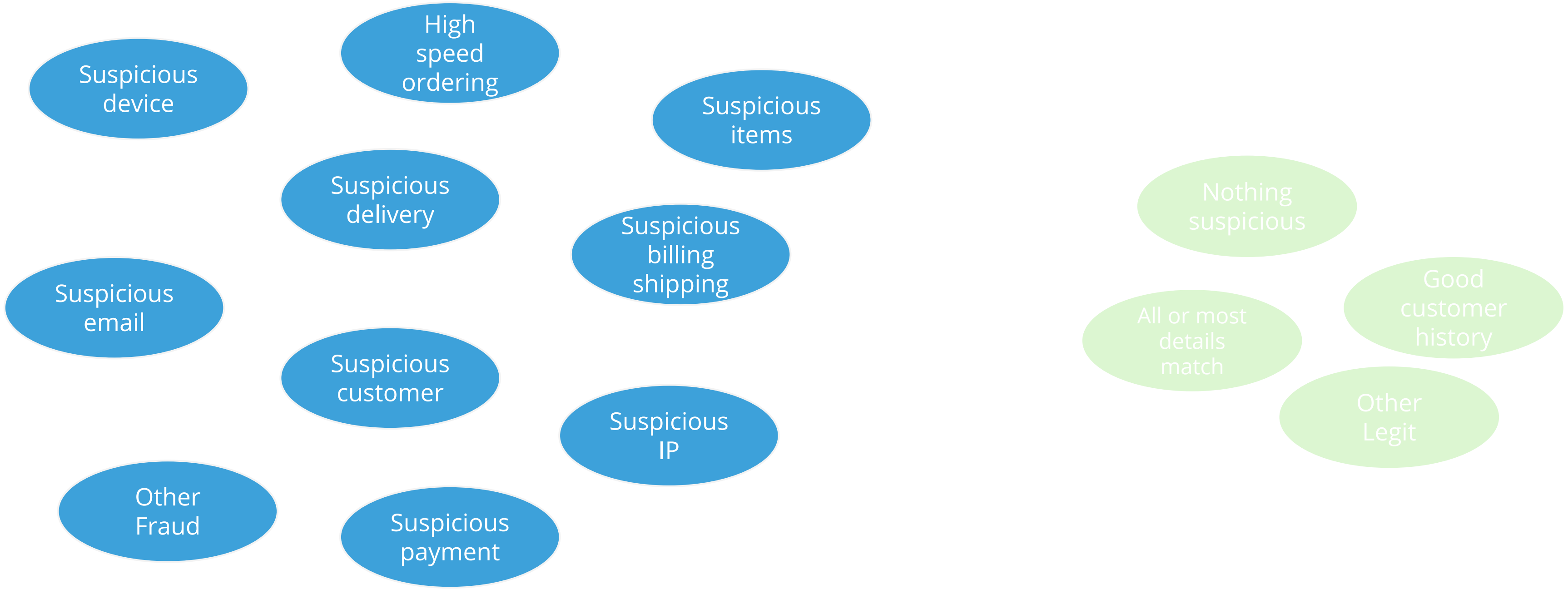


3 **Run a grid search to find the best hyperparameters for Distant Supervision and Supervised Learning.**



4 **JOEL's online loop generates concept-based explanations and collects human feedback in a fraud detection setting.**

Fraud Taxonomy: Fraudulent Concepts

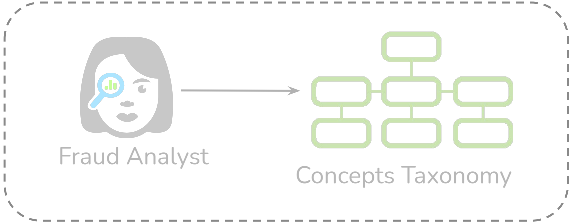


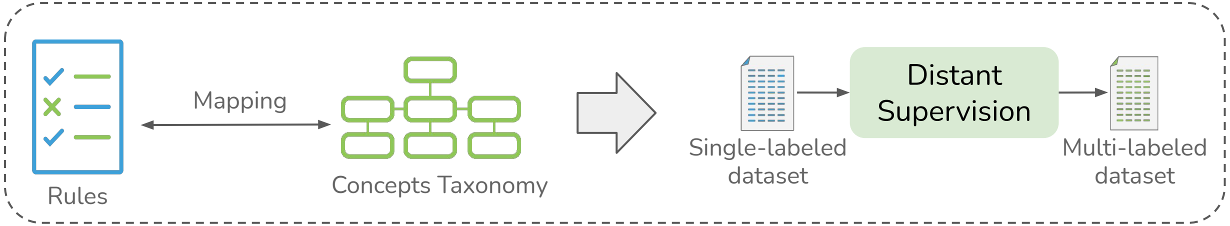
9 Fraudulent concepts (+ **1** Other)

Fraud Taxonomy: Legitimate Concepts

3 Legitimate concepts (+ **1** Other)

Implementation Workflow





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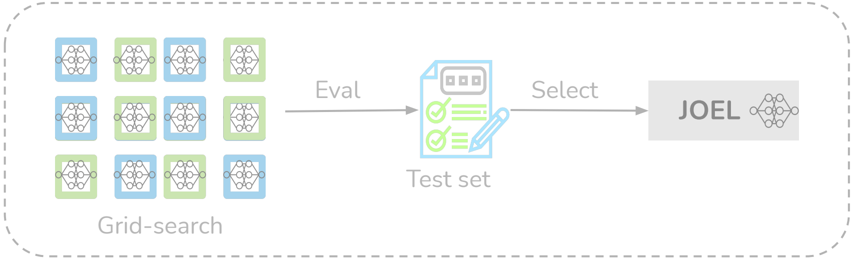

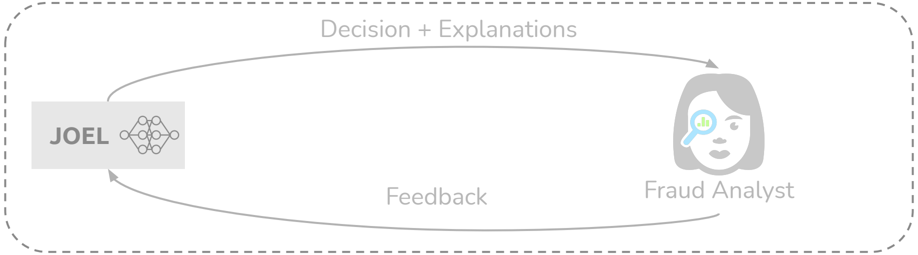

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Tackle Label Scarcity through Weak Supervision

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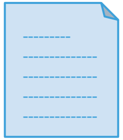
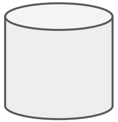
1. Apply a **Distant Supervision** technique using available domain knowledge.

Rules

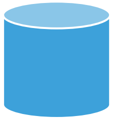




Unlabeled Data
(no concept labels)

Rule-to-Concept Mapping

Rule description	Mapped concepts
Order contains risky product styles.	Suspicious Items
User tried n different cards last week.	Suspicious Customer, Suspicious Payment



Noisy Labeled Data
(weak concept labels)

Concepts Taxonomy

Rules-Concepts Mapping for Distant Supervision

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- One rule can be associated with one or more fraud concepts.

Rules-Concepts Mapping for Distant Supervision

- One rule can be associated with one or more fraud concepts.

- By having a Rules-Concepts mapping, we can use “noisy labels” (mapped concepts) for each transaction using the rules that were triggered.

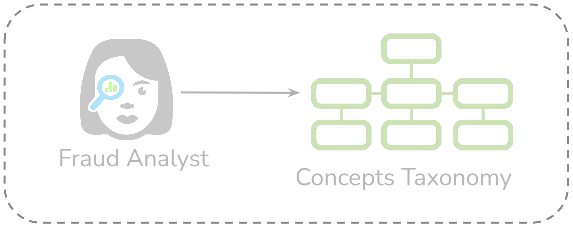
Rules-Concepts Mapping for Distant Supervision

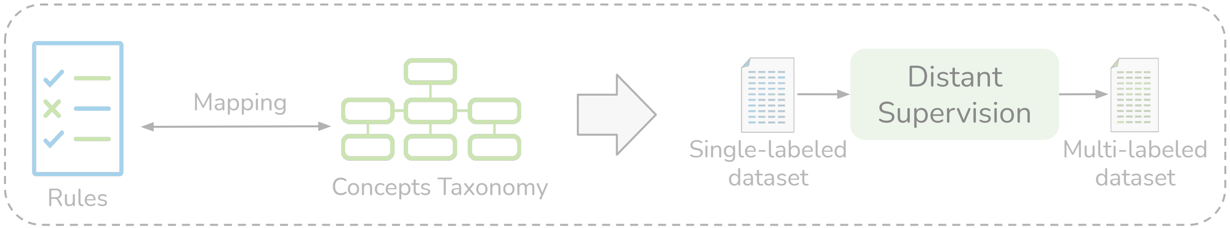
- One rule can be associated with one or more fraud concepts.

- By having a Rules-Concepts mapping, we can use “noisy labels” (mapped concepts) for each transaction using the rules that were triggered.

Canonical rule name	Description	Associated concepts
amount_rule	Transaction amount larger than $N	Suspicious Items
expl_shippingip_mismatch	Shipping and IP mismatch	Suspicious IP, Suspicious billing shipping
jp__card_id_count_N__K_m	The payment card id was detected more than N times in less than K minutes.	Suspicious Payment, High speed ordering

Implementation Workflow





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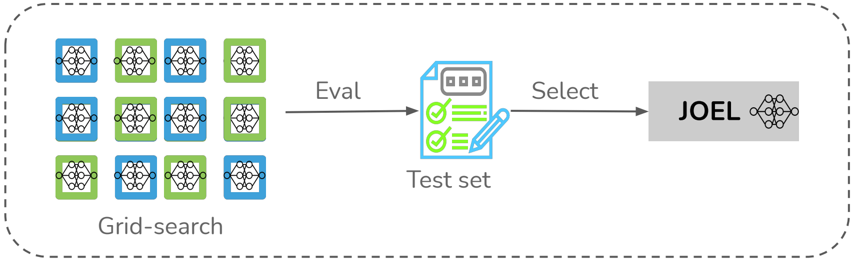

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Jointly learn to explain and decide: Learning Strategies

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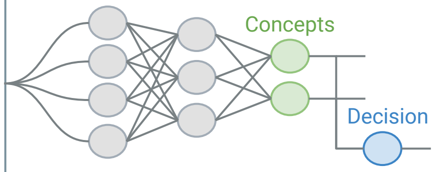
Data → Learning Strategies → Concept-based Explainable Model

Golden Labels

Noisy Labels

A Fully Supervised (Baseline)

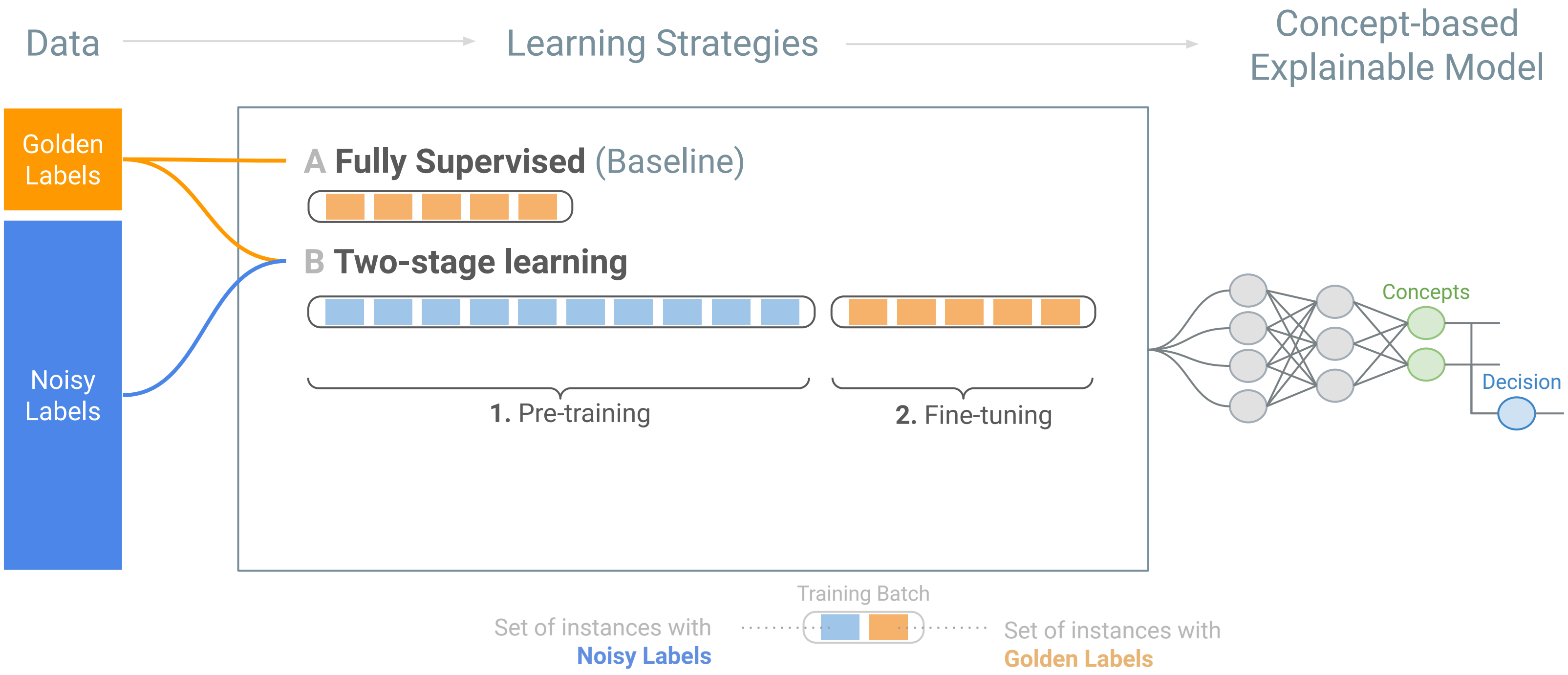


Training Batch

Set of instances with **Noisy Labels**

Set of instances with **Golden Labels**

Jointly learn to explain and decide: Learning Strategies



Jointly learn to explain and decide: Learning Strategies

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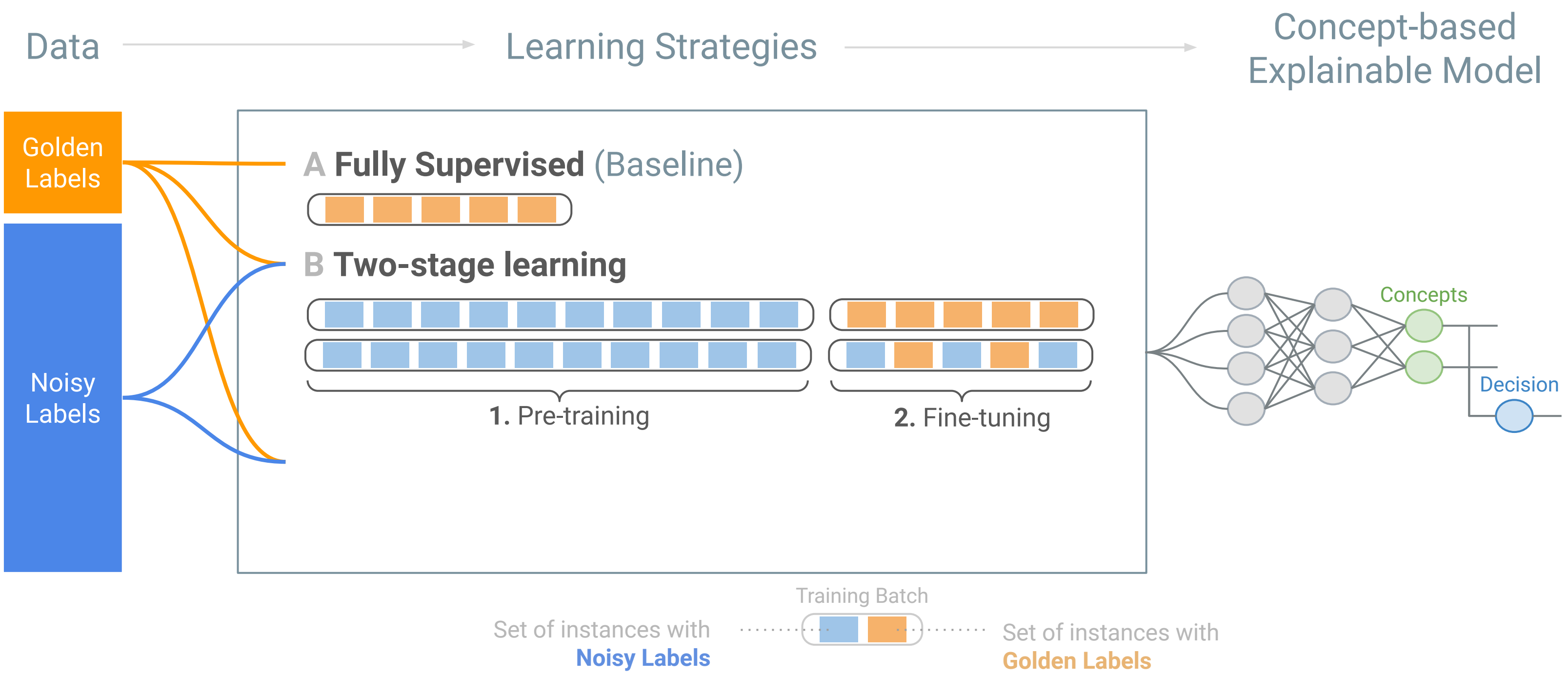

Jointly learn to explain and decide: Learning Strategies

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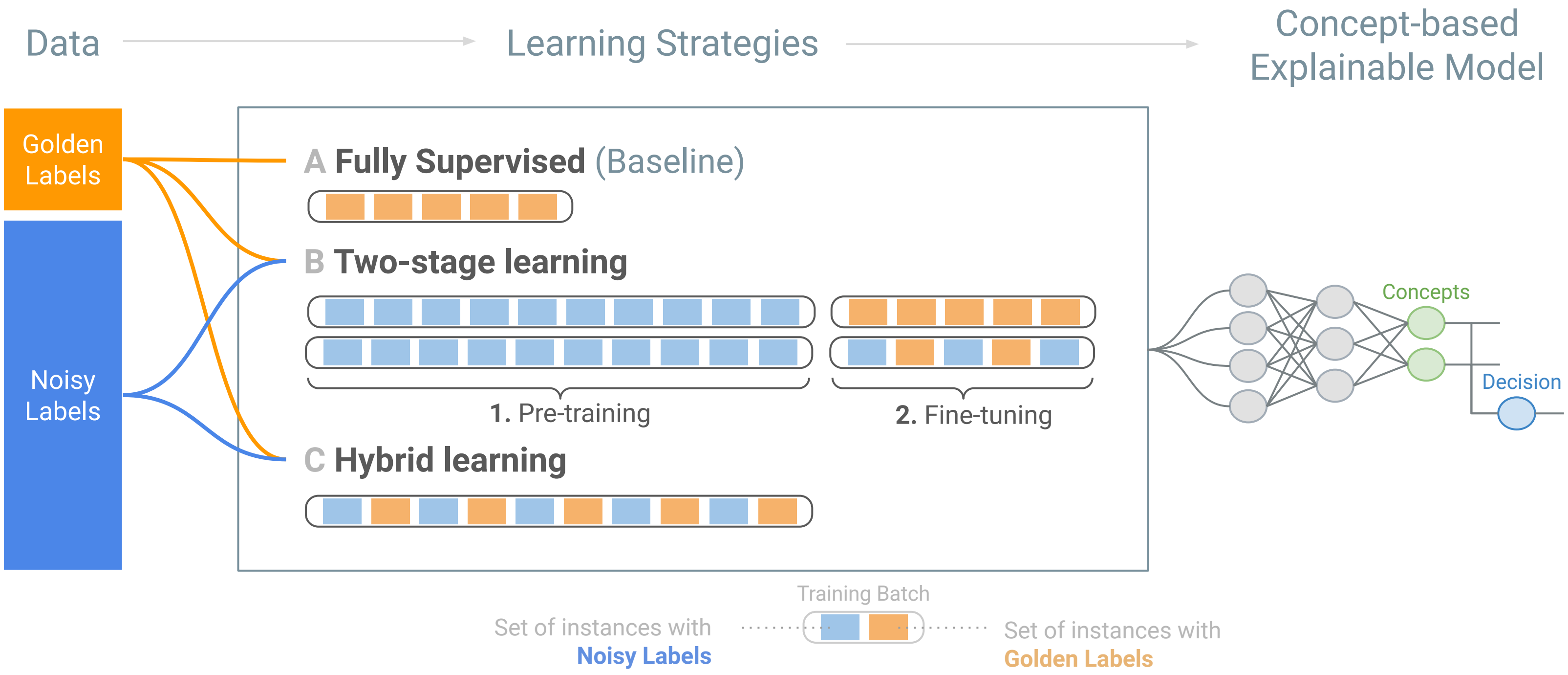
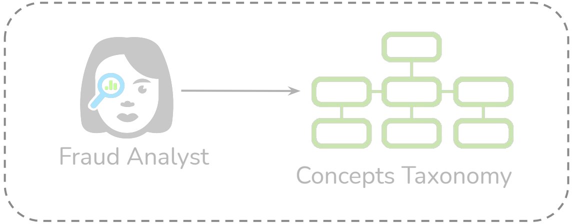
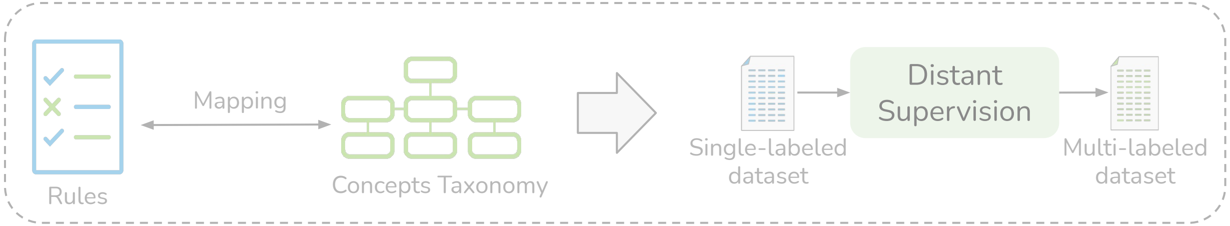


Implementation Workflow





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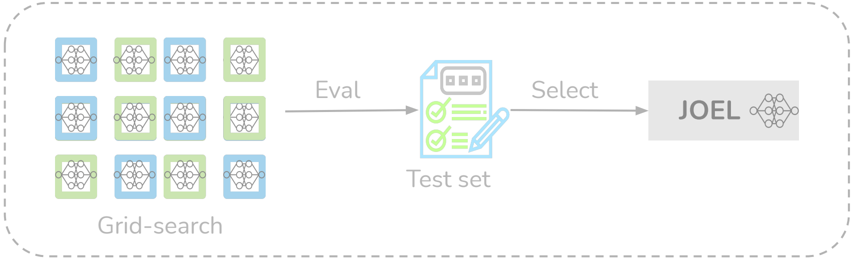

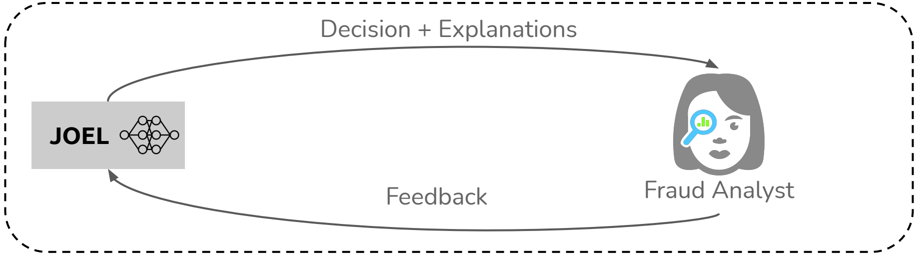

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Human Feedback

- JOEL's explanations and prediction are shown to analyst through Web UI;
- A human-in-the-loop (*e.g.*, fraud analyst) makes a decision based on this information;
- When submitting its review, it also gives feedback about the concepts that led to his decision (and also about the decision task);
- This feedback can be used to continuously improve predictive accuracy, and also explainability of the model.

Experiments

Experimental Setup

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Payment retailer aims to deploy multi-task approach for concept-based explanations.

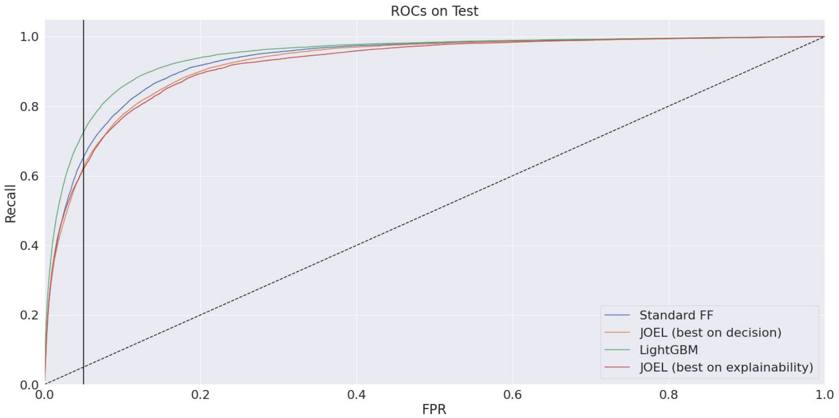
- **Binary decision task**: detect fraudulent transactions;
- **Multi-Label explainability task** (with 14 concepts): output high-level explanation about the model's prediction.

Labels	Availability
Golden decision	High (~6M, ~2% fraud rate)
Noisy Explainability	High (~6M, ~2% fraud rate)
Golden* explainability	Low (~1.3k, ~37% fraud rate)

Evaluation Metrics

Decision Task

Fraud recall @ 5% FPR



Explainability Task

Mean Average Precision (mAP)

$$AP = \frac{\sum_{k=1}^{n}(P(k) * rel(k))}{number\ of\ relevant\ items}$$

$$MAP = \frac{1}{Q}\sum_{q=1}^{Q} AP(q)$$

Hyperparameter & Model Selection

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*Can we **do better** than the **fully supervised** and **low-resources** baseline?*

Model development:

- Run the same hyperparameter grid for each variant;
  (*i.e.*, number and dimension of hidden layers, learning rate, explainability task importance)

- Run 2 random seeds.

Fully Supervised (baseline) - Test set

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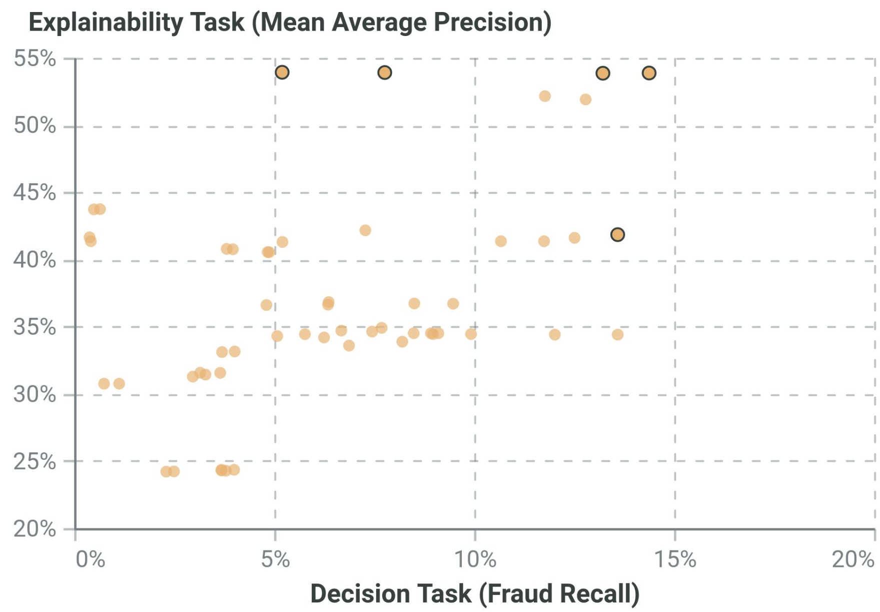
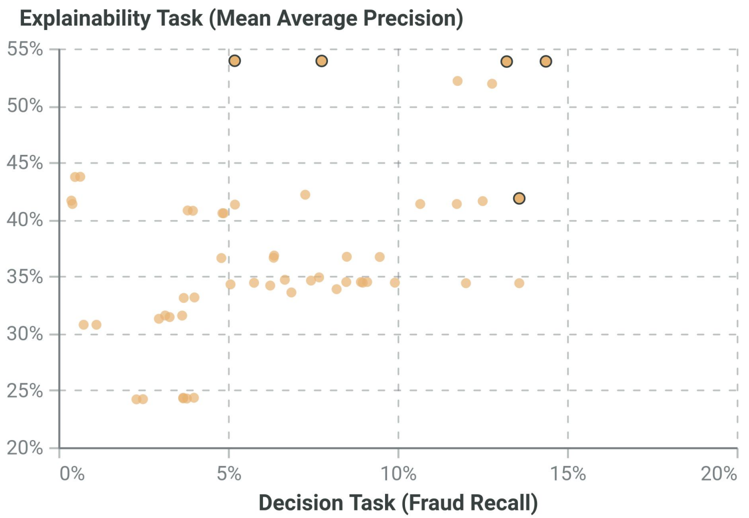


Full supervised learning on a small dataset yields **poor results** in the decision task.

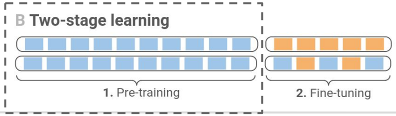
Fully Supervised (baseline) - Test set

A **Fully Supervised** (Baseline)



	Full Supervision
Recall	[0.04; 0.15]
mAP	[0.52; 0.54]

Two-stage learning - Test set



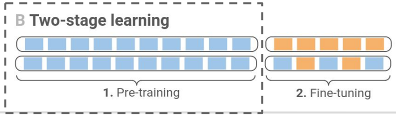
First stage:
Train base models using
Distant Supervision (Noisy Labels).

Second stage:
Fine-tune base models with
Golden Labels.

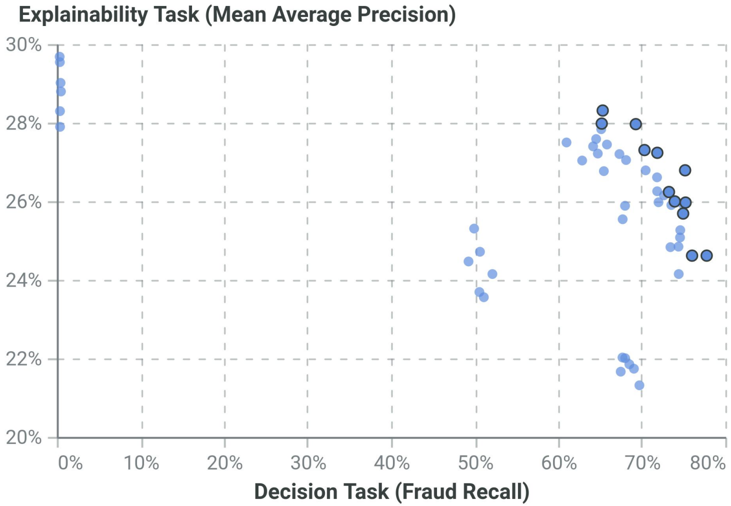
Main goal:
improve **explainability** task
without hurting the **decision** task.

	Full Supervision	Two-stage (base models)	Two-stage (w/ fine tuning)
Recall	[0.04; 0.15]		
mAP	[0.52; 0.54]		

Two-stage learning - Test set



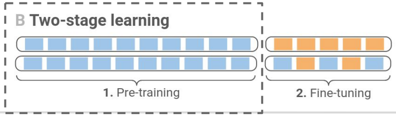
Base models (random seeds 10 and 42)



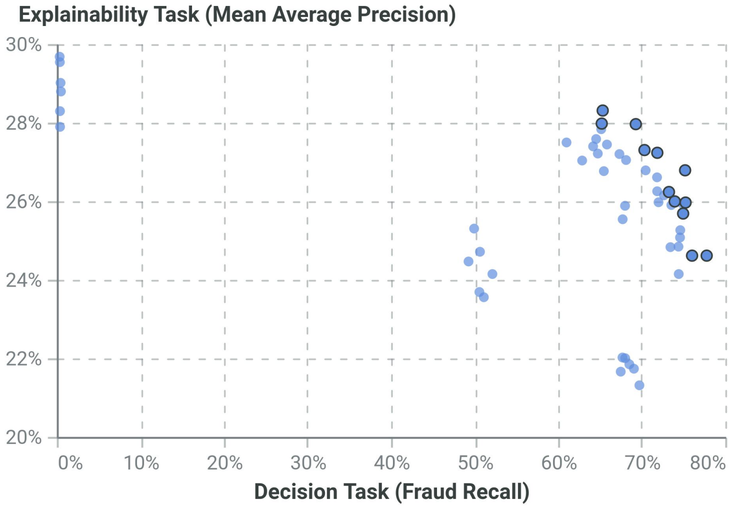
	Full Supervision
Recall	[0.04; 0.15]
mAP	[0.52; 0.54]

- Explainability performance degrades when using the larger but noisy explainability dataset.
- Training with larger dataset improves decision task;

Two-stage learning - Test set

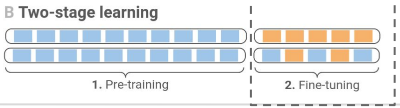


Base models (random seeds 10 and 42)



	Full Supervision	Two-stage (base models)
Recall	[0.04; 0.15]	[0.6; 0.78]
mAP	[0.52; 0.54]	[0.24; 0.29]

Two-stage learning - Test set

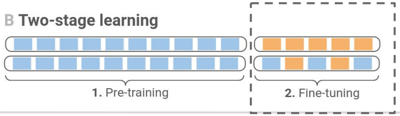


Second stage:
Fine-tune base models with Golden Labels.

Main goal:
improve **explainability** task without hurting the **decision** task.

	Full Supervision	Two-stage (base models)	Two-stage (w/ fine tuning)
Recall	[0.04; 0.15]	[0.6; 0.78]	
mAP	[0.52; 0.54]	[0.24; 0.29]	

Two-stage learning - Test set



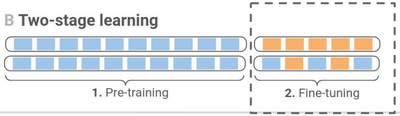
First stage:
Train base models using Distant Supervision (Noisy Labels).

SELECT PARETO MODELS

Second stage:
Fine-tune base models with Golden Labels.

Main goal:
improve **explainability** task without hurting the **decision** task.

Two-stage learning - Test set



Pick **Pareto Optimal** models from Stage 1.

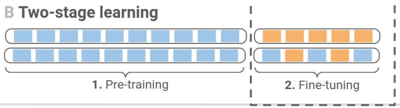
Fine-tune them with:

- Hyperparameters;
  (*e.g.*, learning rate, epochs, batch size)
- Loss scalers;
  (*e.g.*, 0.75, 0.5, 0.25)
- Freeze and unfreeze of layers;
- Different batch techniques.
  (*e.g.*, hybrid batching - add % of noisy labels in each batch)

Second stage:
Fine-tune base models with Golden Labels.

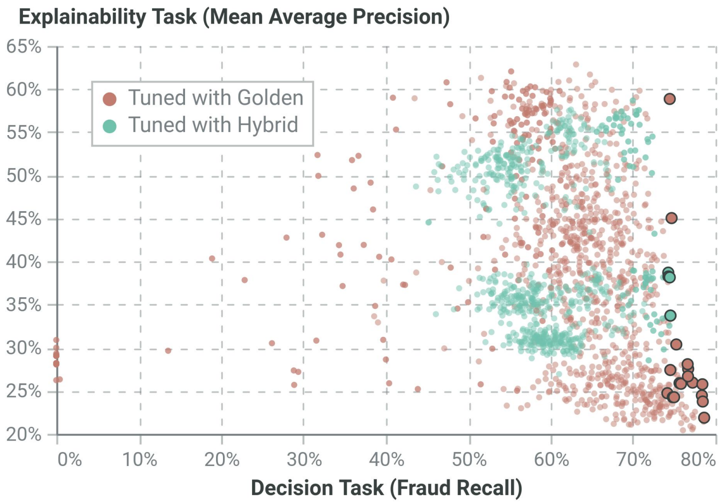
Main goal:
improve **explainability** task without hurting the **decision** task.

Two-stage learning - Test set



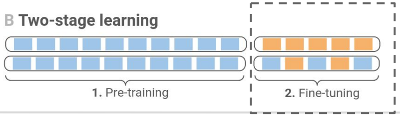
Base models (random seeds 10 and 42)

Fine-tuned models



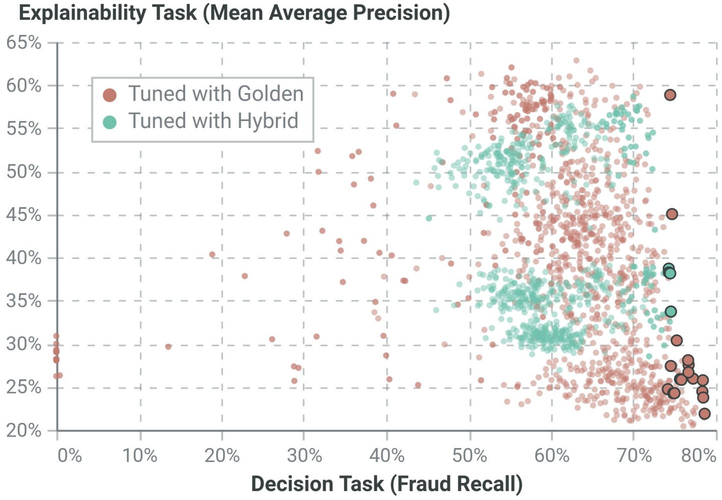
For same decision task performance, we can improve explainability task.

Two-stage learning - Test set



Base models (random seeds 10 and 42)

Fine-tuned models



	Full Supervision	Two-stage (base models)	Two-stage (w/ fine tuning)
Recall	[0.04; 0.15]	[0.6; 0.78]	[0.74; 0.78]
mAP	[0.52; 0.54]	[0.24; 0.29]	[0.24; 0.63]

Hybrid learning - Test set

Each training batch contains a fraction of Explainability Golden Labels (Our experiments use 10%).

Hybrid learning - Test set

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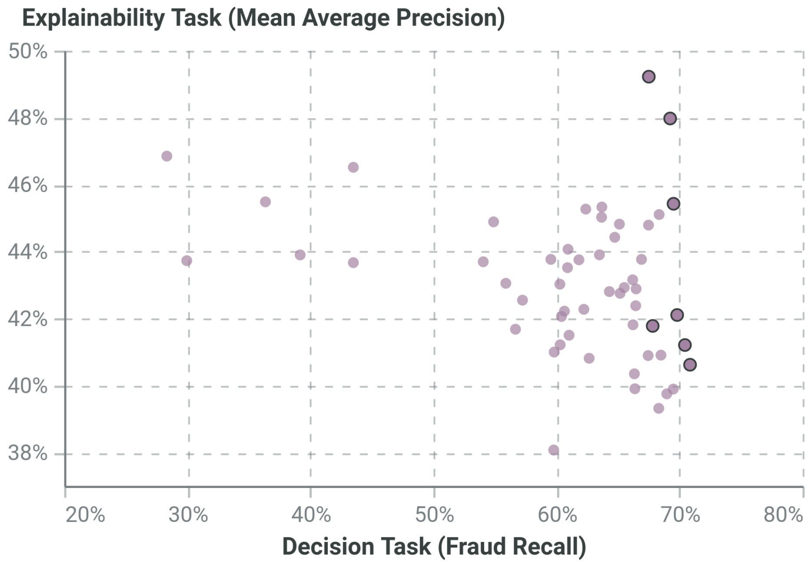
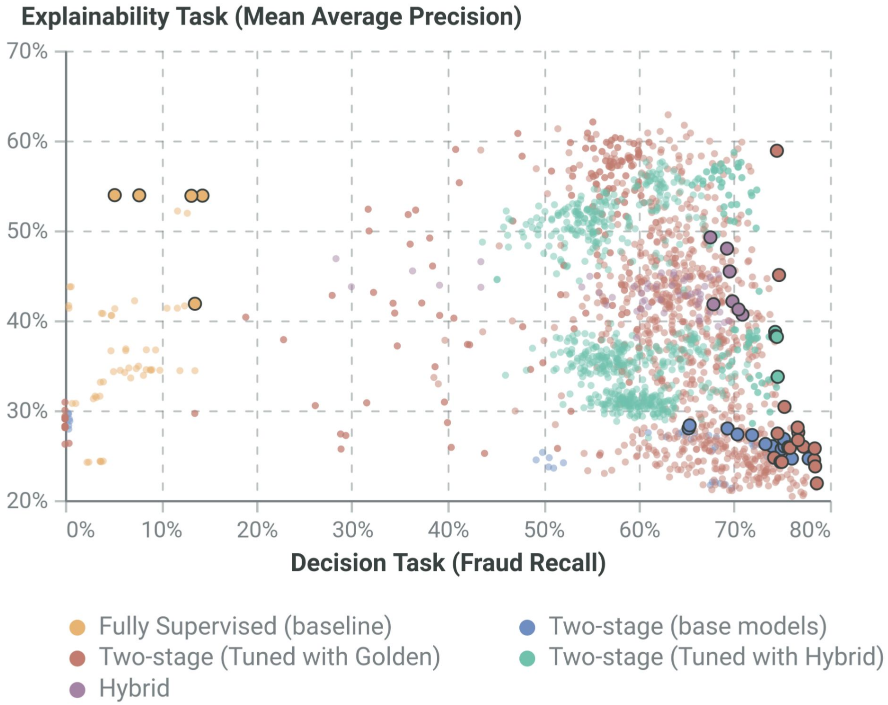


	Full Supervision	Two-stage (base models)	Two-stage (w/ fine tuning)	Hybrid
Recall	[0.04; 0.15]	[0.6; 0.78]	[0.74; 0.78]	**[0.65; 0.71]**
mAP	[0.52; 0.54]	[0.24; 0.29]	[0.24; 0.63]	**[0.4; 0.49]**

Better than **fully supervised** in decision and **two-stage base** models in explainability, but seems to be worse than **two-stage fine-tuned**.

All Pareto from learning strategies - test set



Preliminary results seem to be **promising** but further experiments (more seeds and more runs) to gain statistical confidence.

Conclusions

Recap

- Concept-based explainability through multi-task learning poses challenges:
    - Label scarcity;
    - Joint learning of decision and associated explanations.

- This work proposes to:
    - Use Distant Supervision and exploit the available off-the-shelf domain knowledge;
    - Use different Learning Strategies and combine label qualities to improve performance at both tasks.

Conclusions

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- The explanations should be tailored to the persona's knowledge and task performed;
  - Concept-based explanations are suitable to domain experts that make ML-informed decisions but lack ML knowledge!

- Experiment in a real-world e-commerce fraud detection dataset show:
  1. JOEL is able to learn both domain concept explanations and fraud decisions;
  2. Distant supervision allows us to overcome the label scarcity problem;
  3. There is no clear winner learning strategy.
     (it might depend on business requirements)

Thank you!

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Questions?

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