# Stanford CS224W: Relational Deep Learning

CS224W: Machine Learning with Graphs
Charilaos Kanatsoulis
Jure Leskovec, Stanford University

http://cs224w.stanford.edu

# Announcements

- **(11/7) Colab 3** is due today
- **(11/7) Project Milestone** is due today
- **(11/14) Homework 3** is due in a week
  - Keep an eye out on Ed – HW3 recitation will happen this weekend (Sat Afternoon)
- Colab 4 will be released today (due after thanksgiving break)
- **The exam is coming up (in 2 weeks) - we just released the practice exam on ed.**

# Response to high-frequency feedbacks

- **Extended Office hour**

We have added 6 hours of additional OH for the next two weeks. Check out here for schedule: https://edstem.org/us/courses/67691/discussion/5651218

- **Early Release of Practice Exam**

The practice exam is released today! It is available here:https://edstem.org/us/courses/67691/discussion/5664636

Stay tuned for practice exam recitation time soon!

# Stanford CS224W: Relational Databases

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# Deep Learning Revolution

## Sequences

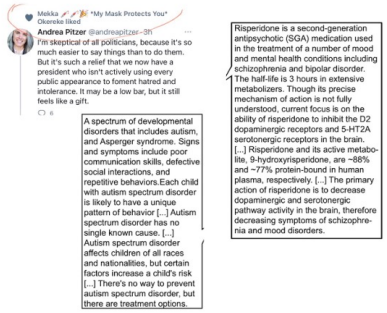
Statue of Liberty

Article Talk

From Wikipedia, the free encyclopedia

*For other uses, see Statue of Liberty (disamb*

The **Statue of Liberty** (***Liberty Enlightening the World***; French: *La Liberté éclairant le monde*) is a colossal neoclassical sculpture on Liberty Island in New York Harbor in New York City, in the United States. The copper statue, a gift from the people of France, was designed by French sculptor Frédéric Auguste Bartholdi and its metal framework was built by Gustave Eiffel. The statue was dedicated on October




A spectrum of developmental disorders that includes autism, and Asperger syndrome. Signs and symptoms include poor communication skills, defective social interactions, and repetitive behaviors.Each child with autism spectrum disorder is likely to have a unique pattern of behavior [...] Autism spectrum disorder has no single known cause. [...] Autism spectrum disorder affects children of all races and nationalities, but certain factors increase a child's risk [...] There's no way to prevent autism spectrum disorder, but there are treatment options.

Risperidone is a second-generation antipsychotic (SGA) medication used in the treatment of a number of mood and mental health conditions including schizophrenia and bipolar disorder. The half-life is 3 hours in extensive metabolizers. Though its precise mechanism of action is not fully understood, current focus is on the ability of risperidone to inhibit the D2 dopaminergic receptors and 5-HT2A serotonergic receptors in the brain. [...] Risperidone and its active metabolite, 9-hydroxyrisperidone, are ~88% and ~77% protein-bound in human plasma, respectively. [...] The primary action of risperidone is to decrease dopaminergic and serotonergic pathway activity in the brain, therefore decreasing symptoms of schizophrenia and mood disorders.

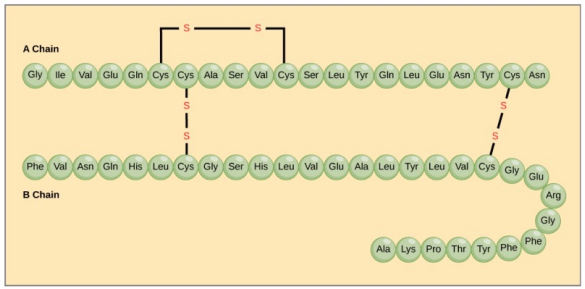
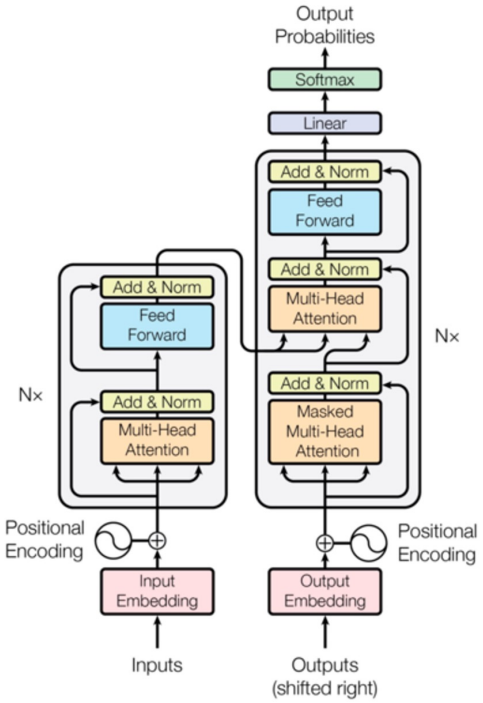


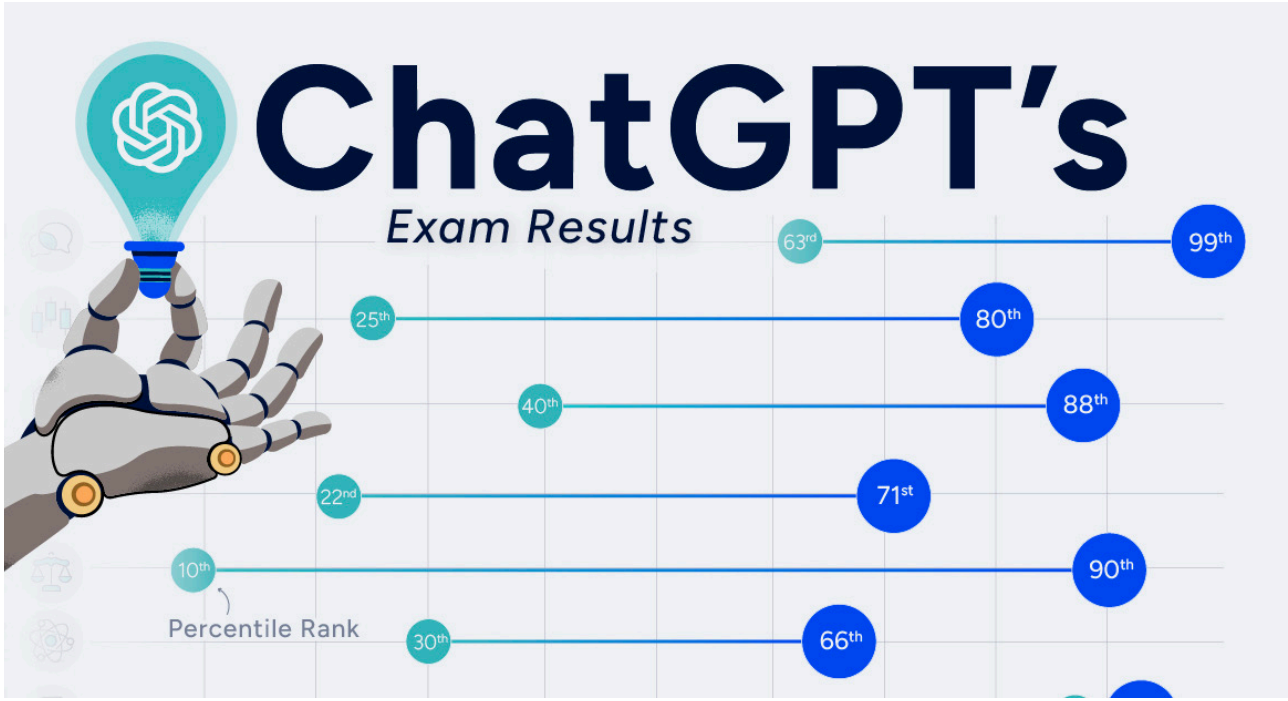

*image credit: OpenStax Biology.*

## Images

# Deep Learning Revolution

These breakthroughs are fueled by Transformers

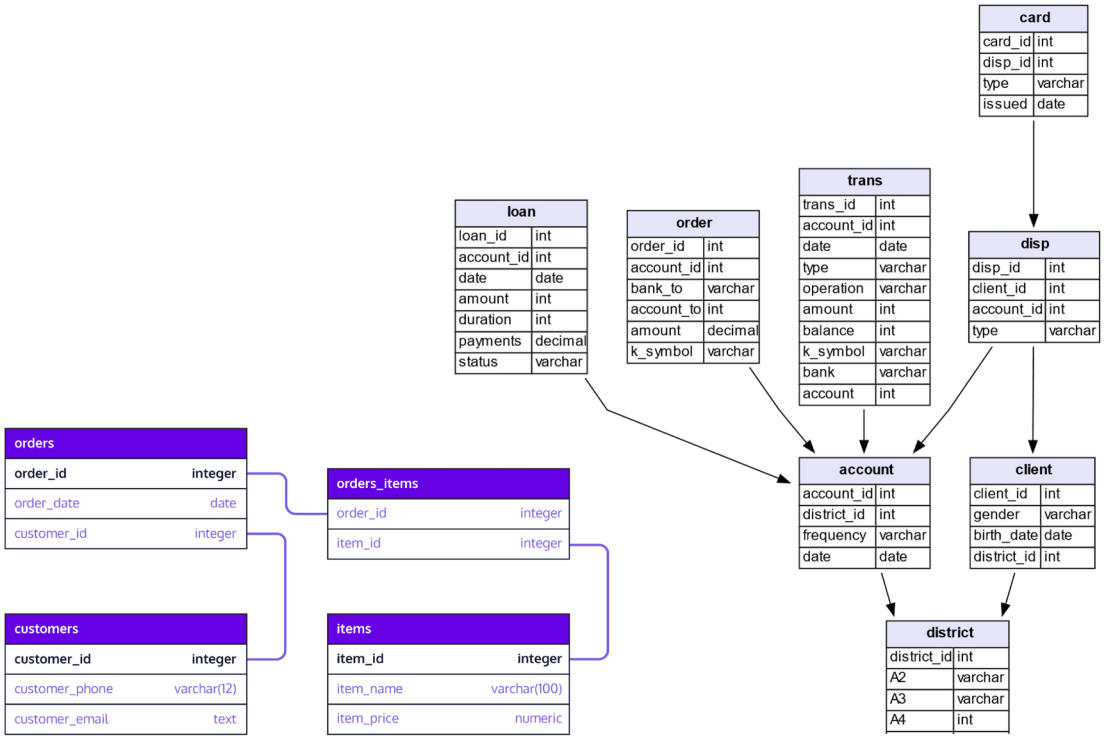


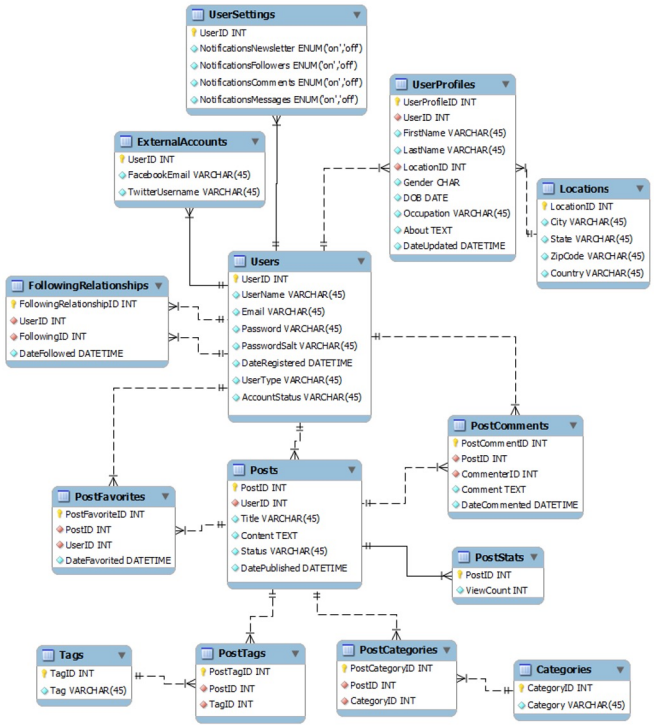



# Deep Learning Revolution

These breakthroughs are fueled by Data

# Data stored in Relational Databases




Commerce

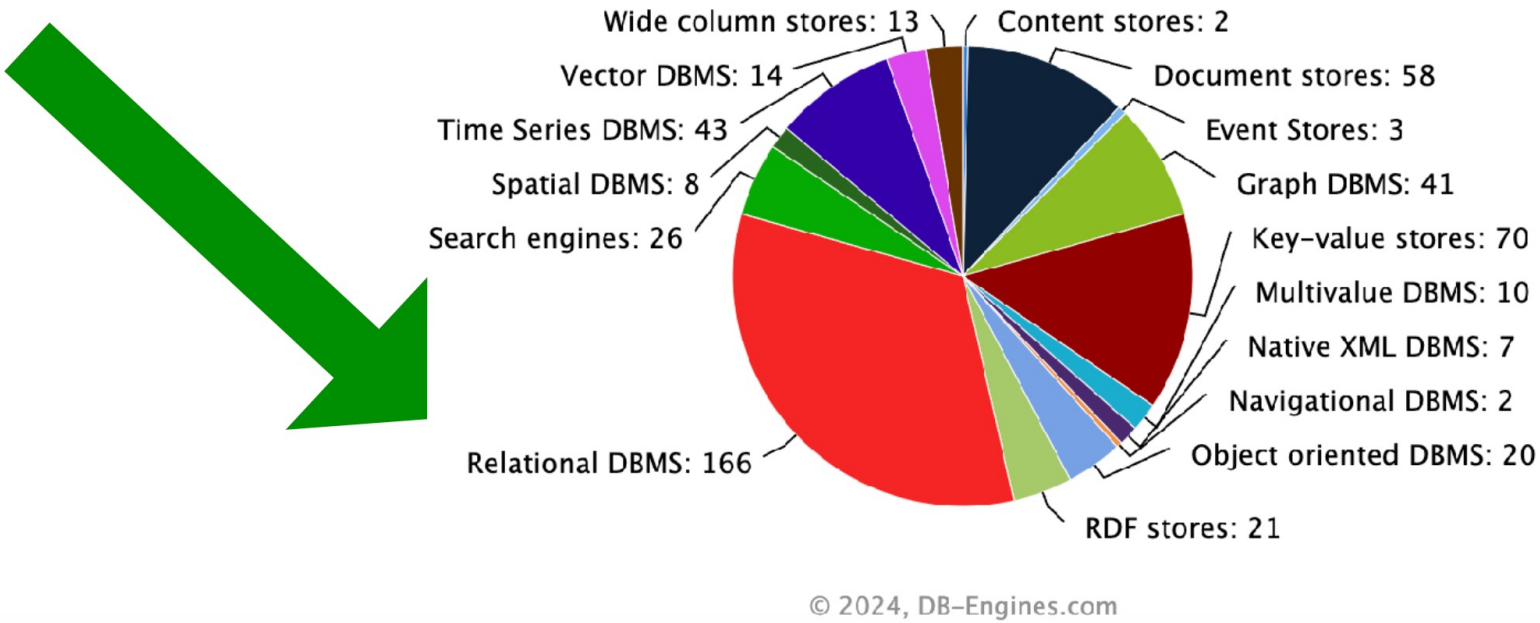
Finance

Social Media

# Database Management Systems

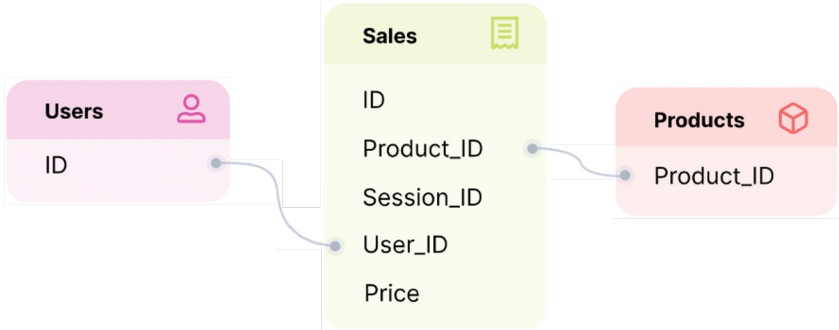
**DBMS popularity broken down by database model**

**Number of systems per category, April 2024**



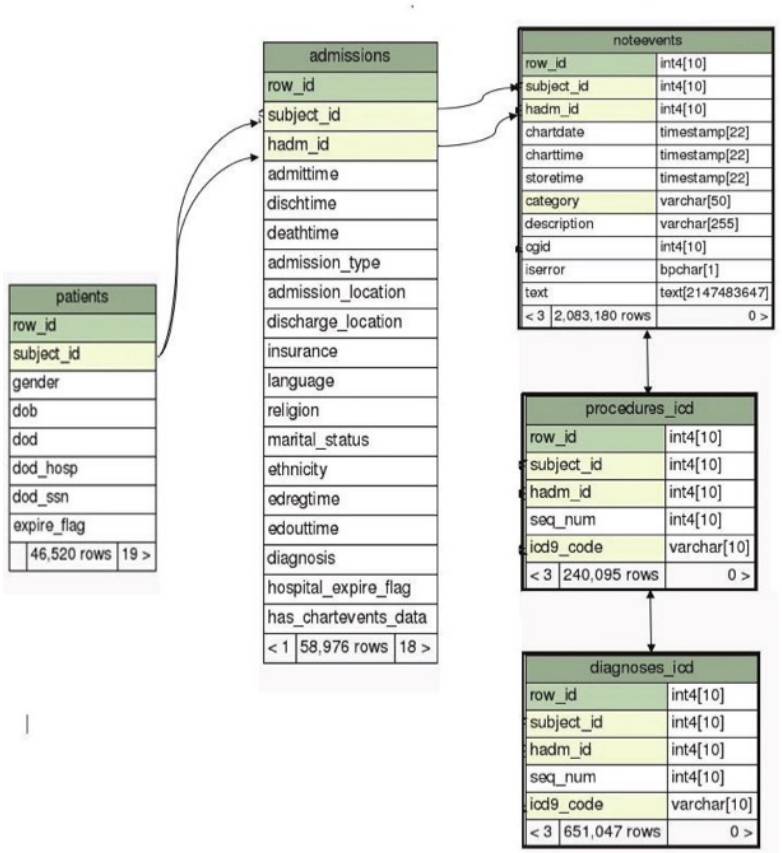
# Predictions on Relational Data

- Which products will a user purchase in the next 7 days?
- Will an active user churn in the next 90 days?
- What will be the total sales for each product in the next 30 days?

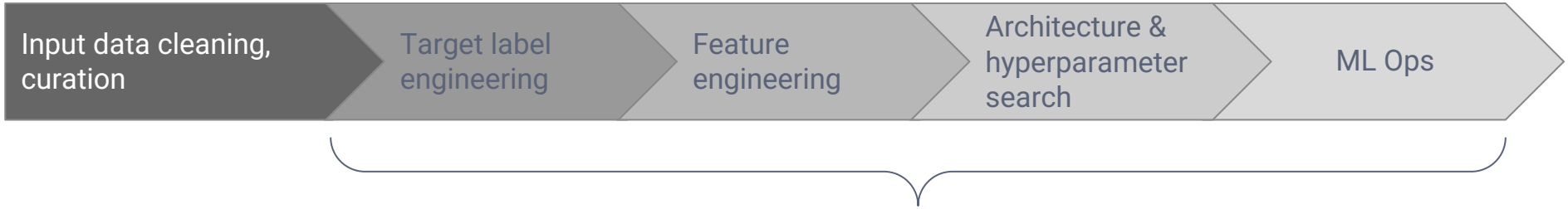


# Predictions on Relational Data

- Will a patient return if discharged from the hospital?
- Which hospital admissions have greatest risk to life in the next 24 hours



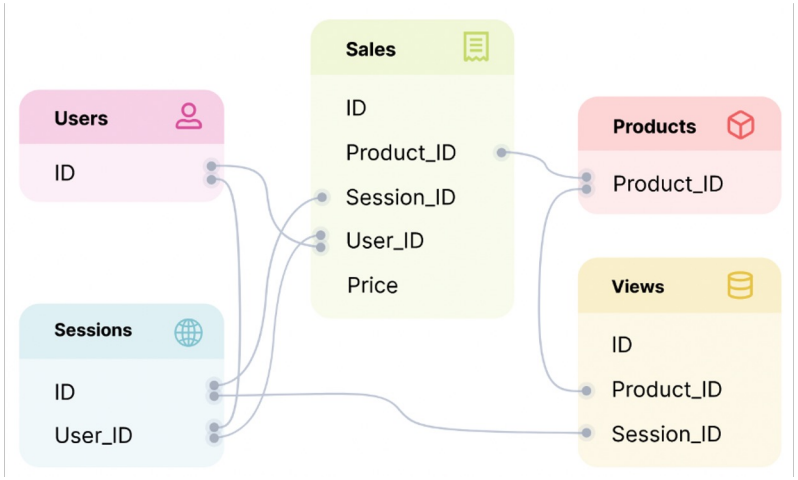
# Doing AI is slow & complex




6-12 months of time for a team of data scientists, data engineers and product engineers

# Impedance Mismatch

Goal: Learn a user churn model based on their sales, purchased products and browsing behavior




Examples

| #monthly sales | sum weekly item price | #orders relative to Sunday | **Label** |
|---|---|---|---|
| … | … | … | … |
| … | … | … | … |
| … | … | … | … |

Features

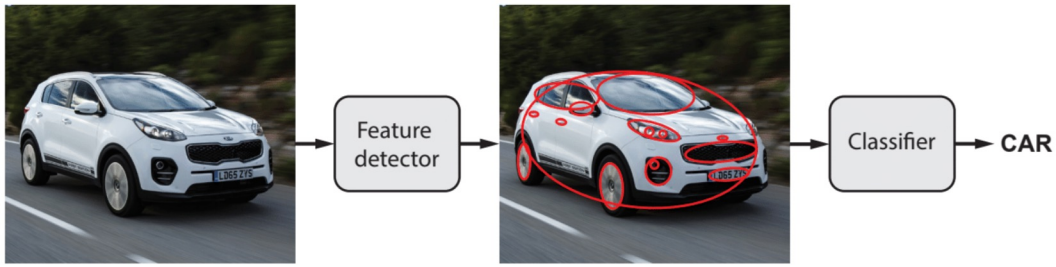
- Features are chosen arbitrarily (*e.g.*, aggregations, time windows)
- Only a limited set of data is used
- Issues with point-in-time correctness/information leakage

# Key Question

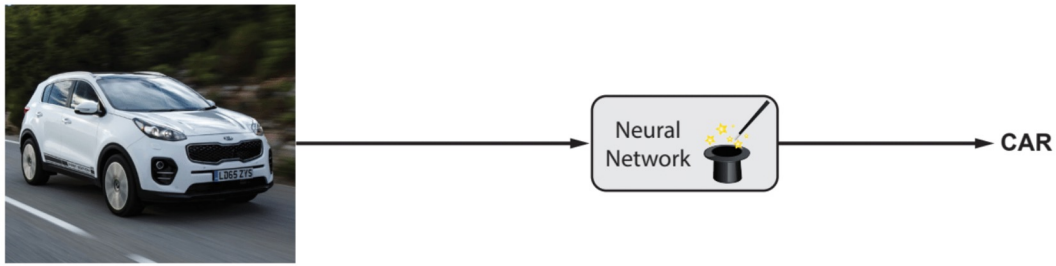
How to leverage the data without going through the longest duration tasks (extraction, transformation, loading)?

**We want ML algorithms that can process data in its natural form!**

# CV moved to end-to-end learning




Classical computer vision: hand-crafted features (e.g. SIFT)
+ simple classifier (e.g. SVM)



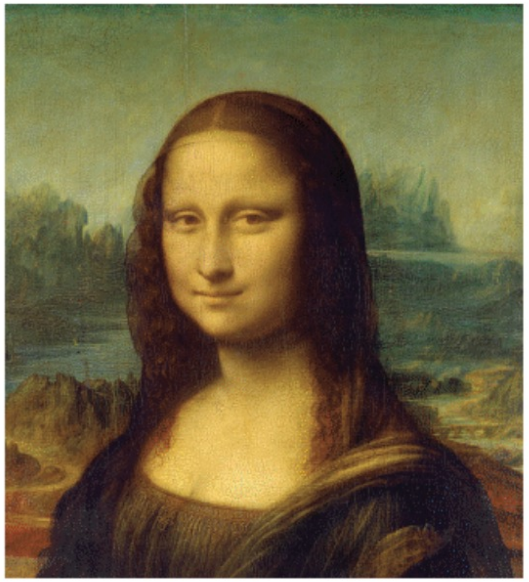

Modern computer vision: data-driven end-to-end systems

# Modern ML

- Today we want to design deep learning models that operate on relational tables
- But modern deep learning toolbox is designed for **different type of inputs**

Doubt thou the stars are fire,
Doubt that the sun doth move,
Doubt truth to be a liar,
But never doubt I love...

Text



Images

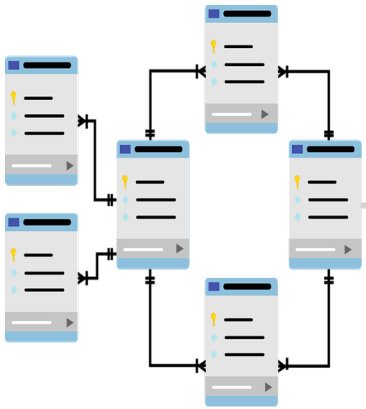
# Stanford CS224W: Generalizing Deep Learning to Databases

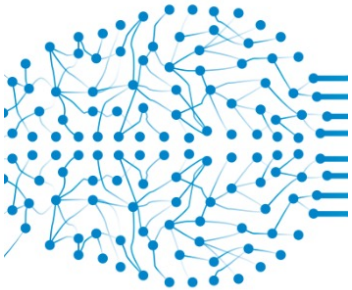
CS224W: Machine Learning with Graphs

Jure Leskovec, Stanford University

http://cs224w.stanford.edu

# Deep Learning on Relational Tables





Relational Deep Learning

**Prediction**

# What is RDL?

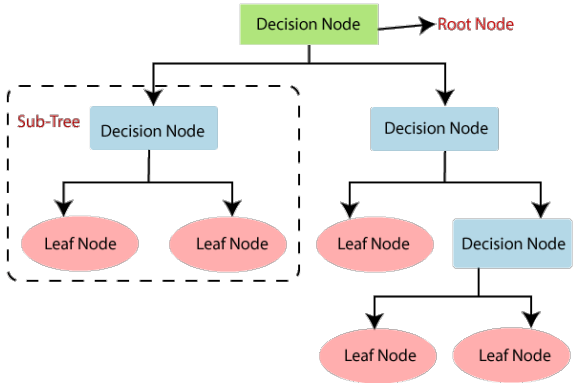
- End-to-end deep learning on relational tables (*i.e.*, databases)
- Works directly on relational tables, no transformations, no feature engineering
- Casts predictive tasks as **graph representation learning** problems

# Impact and Consequences

- More accurate models
  (no feature engineering)
- More robust models
  (model-learned features automatically "update" over time)
- Shorter time to models
  (no mundane ETL work)
- Simpler infrastructure
  (no pipelines, no feature stores, etc.)

# Related Work: Tabular ML

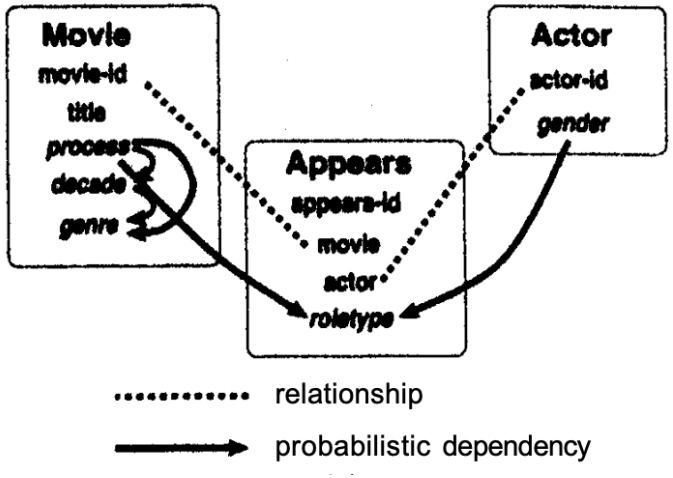
- Great for building models on one table
  - But most data is not a single table!




- Deep learning is not dominant:
  - Hypothesis: Because single table already contains features engineered from other tables (loss of information)
- RDL accounts for relations between multiple tables, unlike tabular ML!

# Related Work: Stat. Rel. Learning

[Friedman et al., 1999]




Learns a distribution (graphical model) over the relational structure

- Predictions via world model + inductive logic programming
- Only works with categorical variables
- Does not scale to large data

- RDL a **scalable, expressive inheritor** of Statistical Relational Learning

# Stanford CS224W: Relational Deep Learning

CS224W: Machine Learning with Graphs
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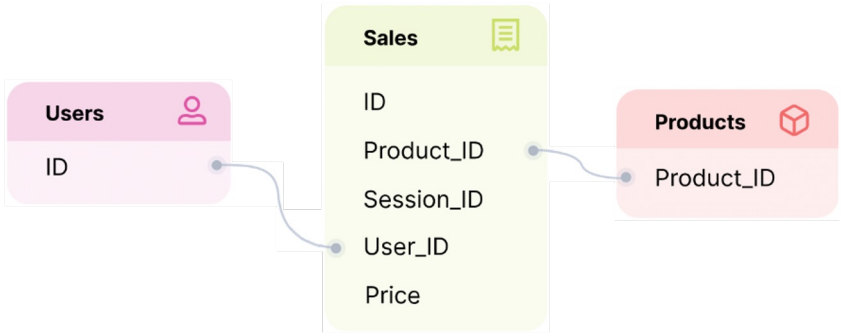
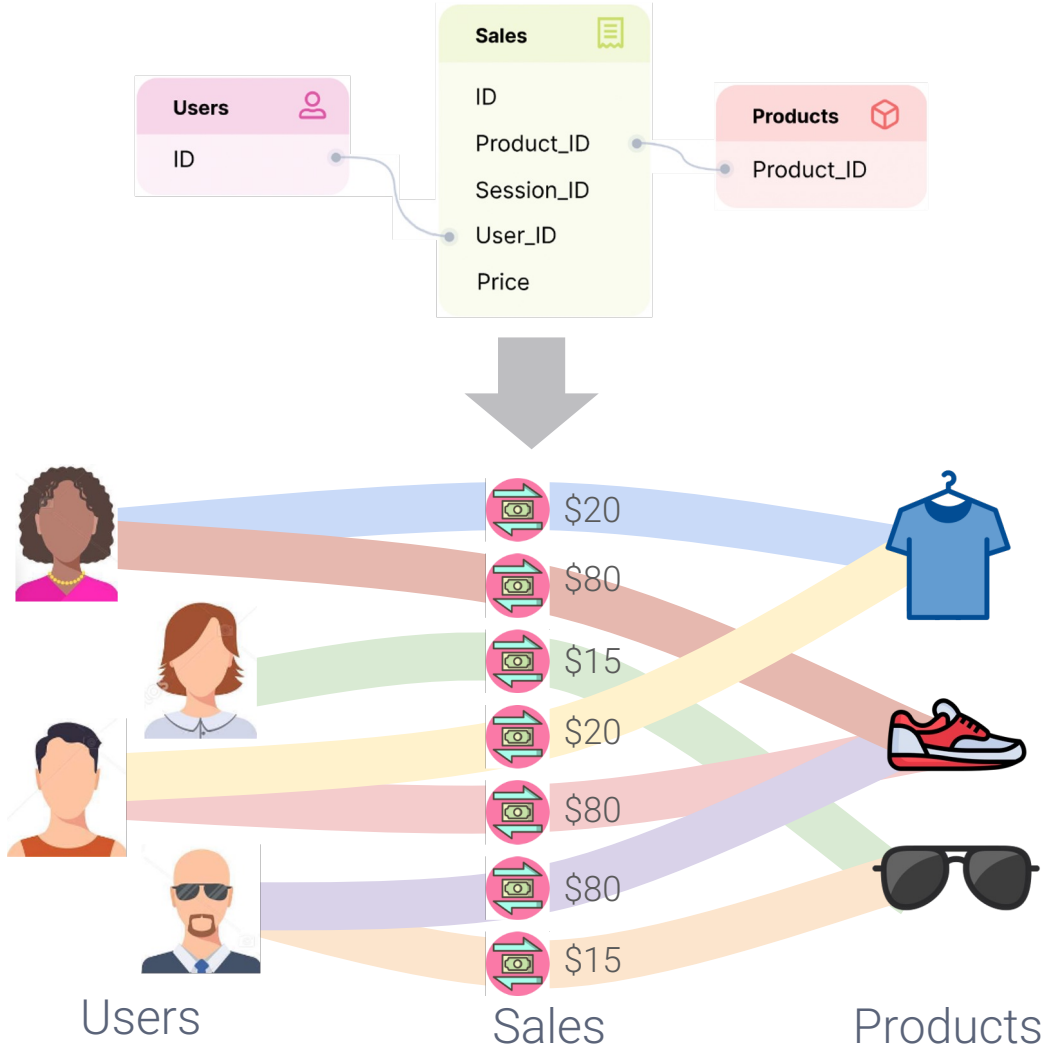
# Insight: A Data is a graph!



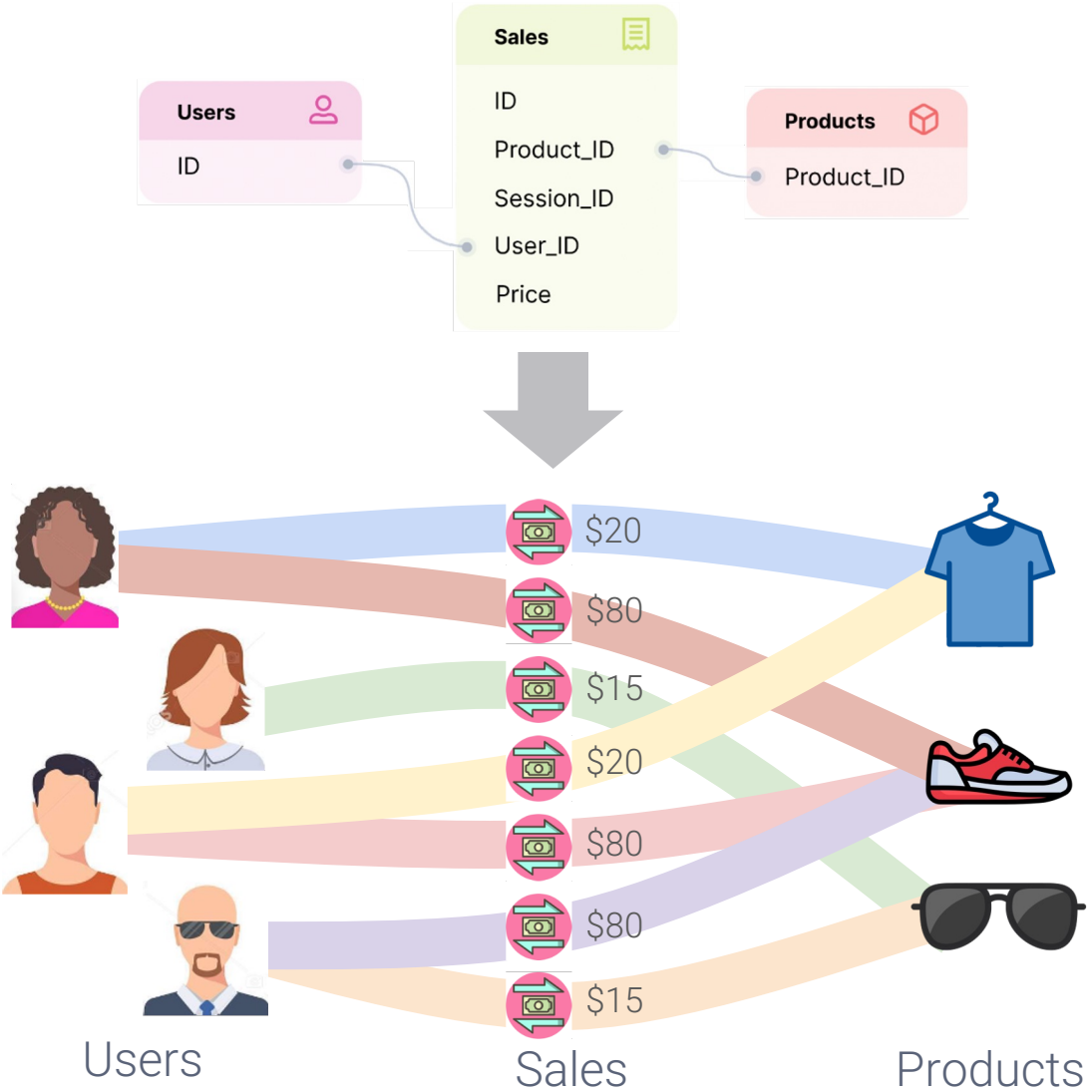
# A Database is a graph!



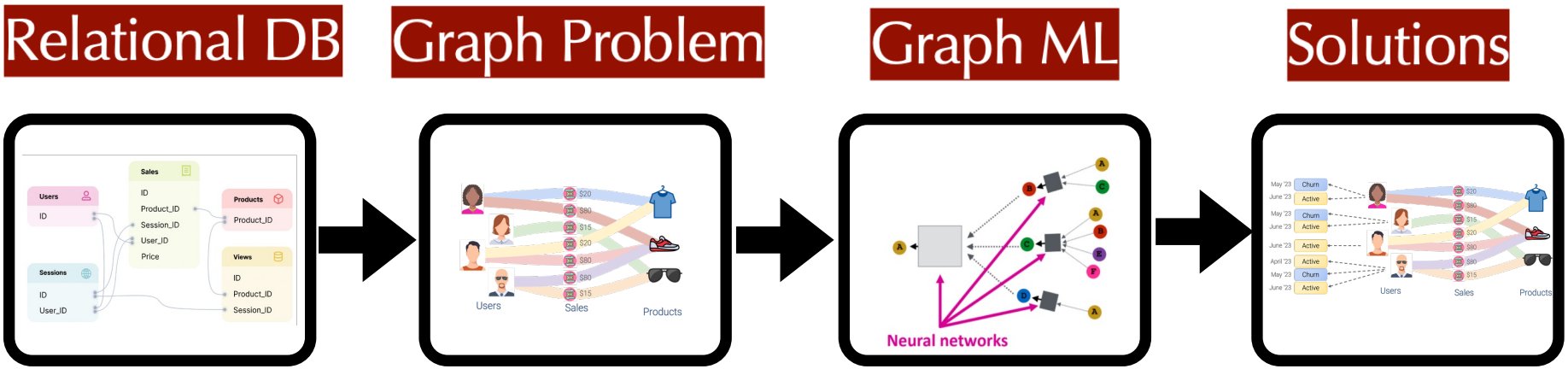
# Just do ML on a Graph!

## ML in the language of graphs:

- Node-level:
  - Churn
  - Life-time value
  - Next best action
- Link-level:
  - Product affinity
  - Recommendations
- Graph-level:
  - Fraud, money laundering



# Graph ML Problem Solving Pipeline



# Stanford CS224W: Relational Database Graph

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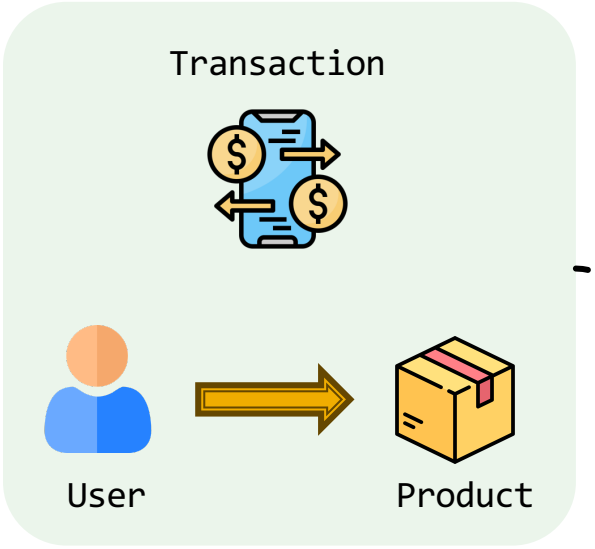
# Databases

## Real-world data are stored in databases

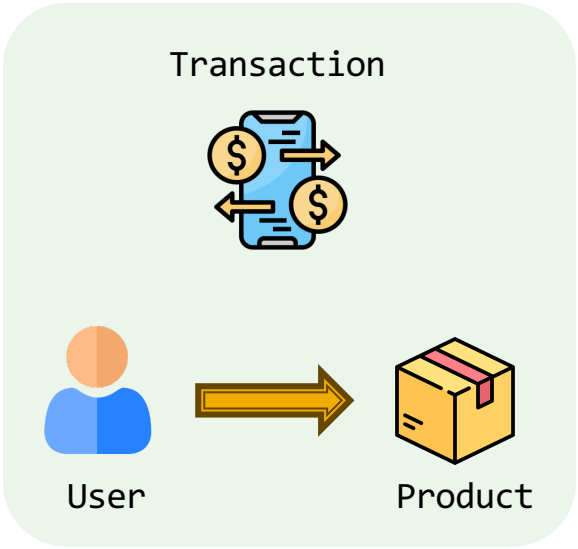



Transaction Table

| Trans ID | User ID | Product ID | Value | Timestamp |
|---|---|---|---|---|
| … | … | … | … | … |
| … | … | … | … | … |
| … | … | … | … | … |
| … | … | … | … | … |
| 100 | 51 | 345 | $1000 | 1710281001 |
| … | … | … | … | … |

# Relational Databases

## Databases are often relational




Transaction Table

| Trans ID | User ID | Product ID | Value | Timestamp |
|---|---|---|---|---|
| ... | ... | ... | ... | ... |
| ... | ... | ... | ... | ... |
| ... | ... | ... | ... | ... |
| ... | ... | ... | ... | ... |
| 100 | 51 | 345 | $1000 | 1710281001 |
| ... | ... | ... | ... | ... |

User Table

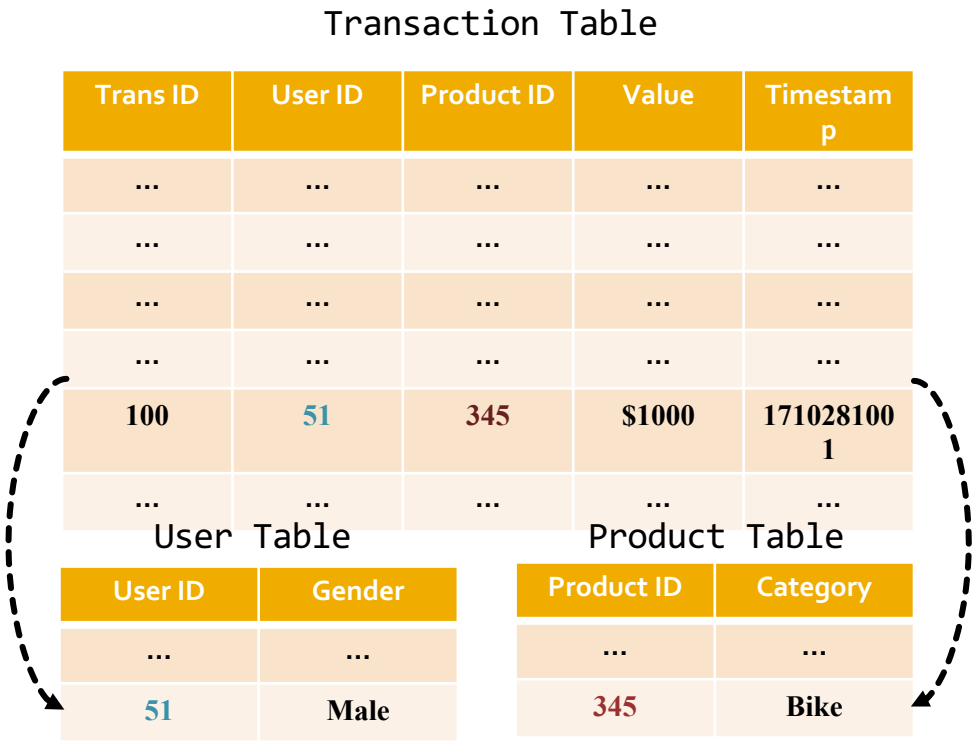
| User ID | Gender |
|---|---|
| ... | ... |
| 51 | Male |

Product Table

| Product ID | Category |
|---|---|
| ... | ... |
| 345 | Bike |

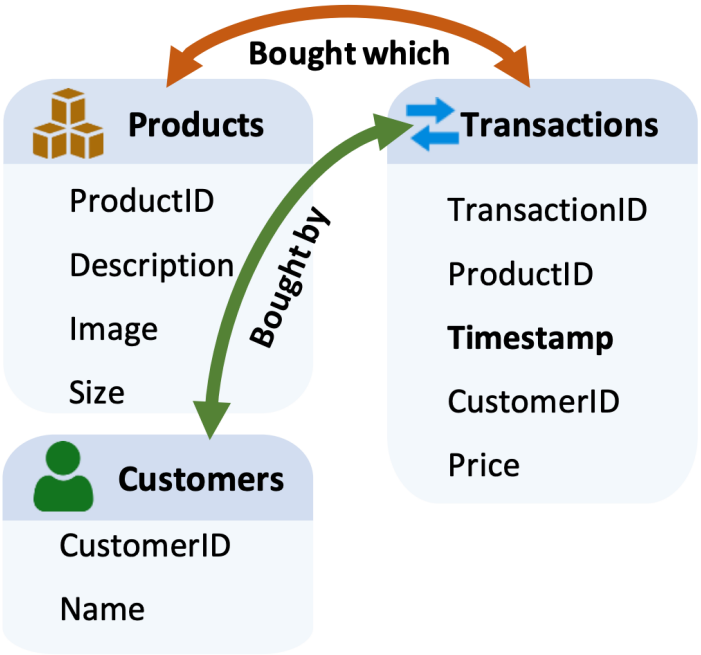
Relational databases as heterogeneous graphs

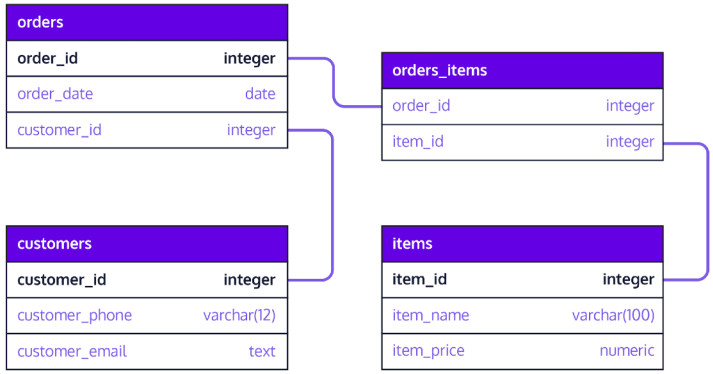
# Mathematically…




- A database is a set of tables $\mathcal{T} = \{T_1, \ldots, T_n\}$ and
- Links between tables $\mathcal{L} \subseteq \mathcal{T} \times \mathcal{T}$

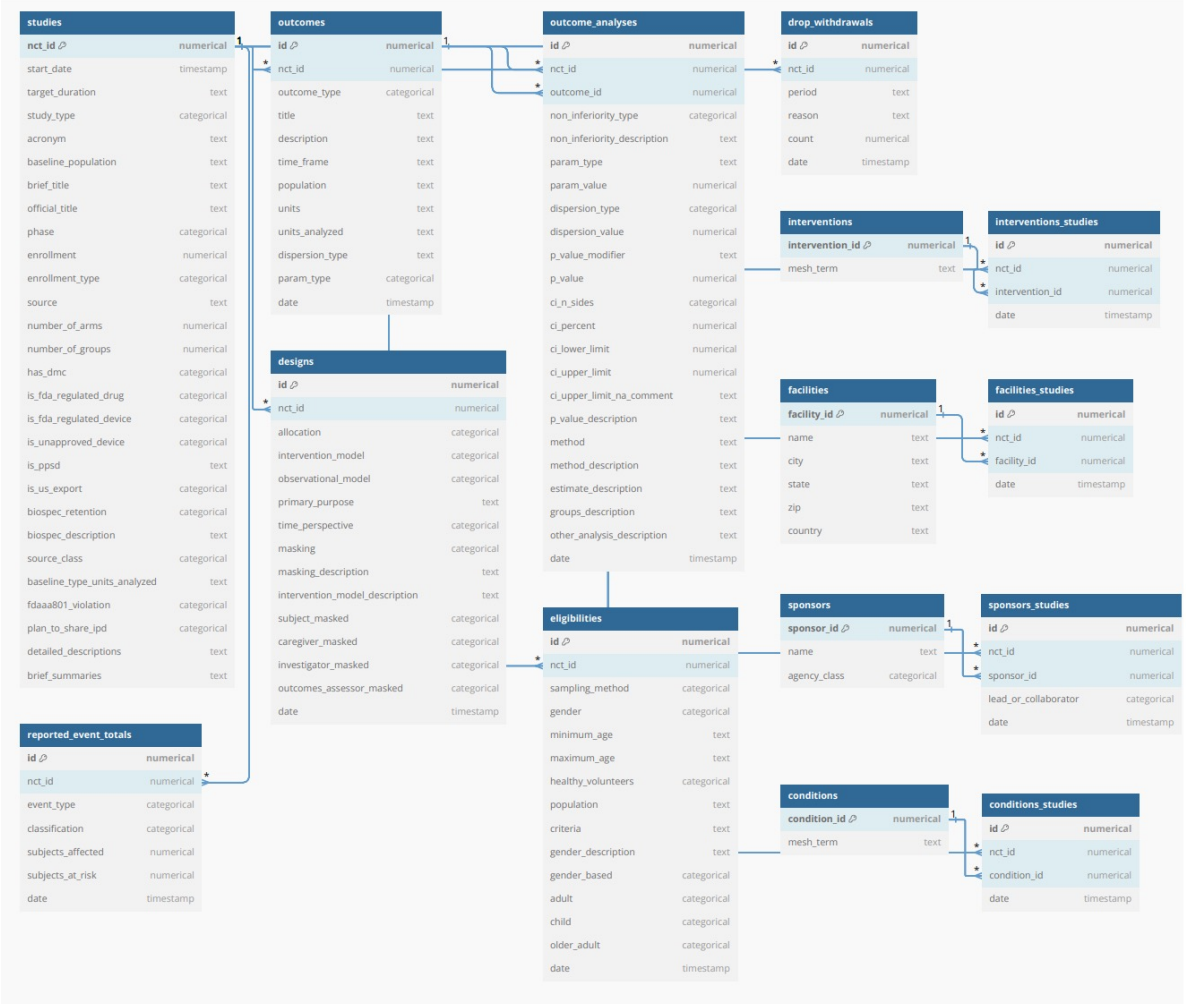
# Schema Graph




- The schema graph represents the high-level structure of the heterogeneous graph

# Rel-trial Schema Graph

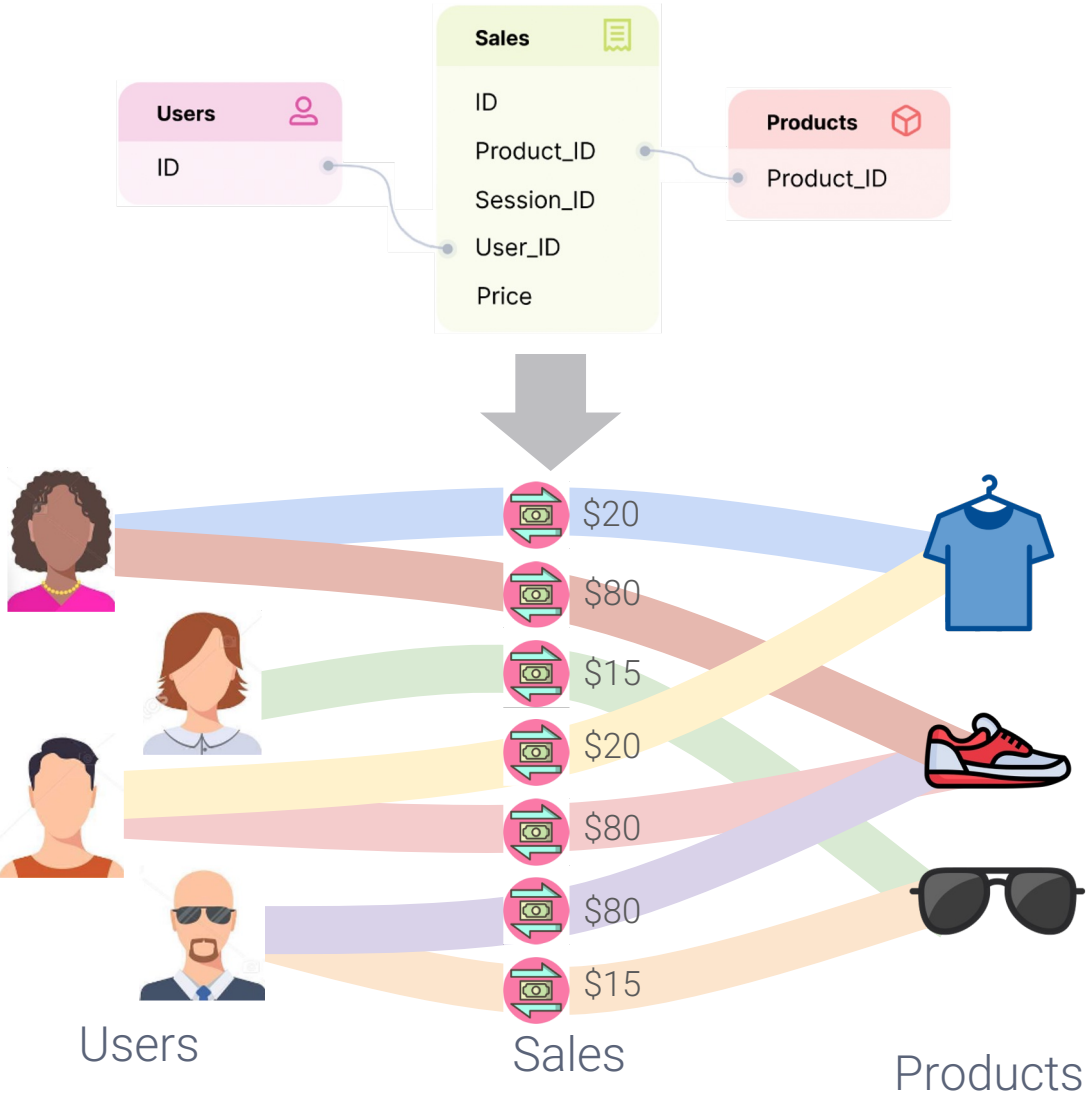



- The schema graphs can be more complex

# Relational Entity Graph

**Relational Entity Graph:**

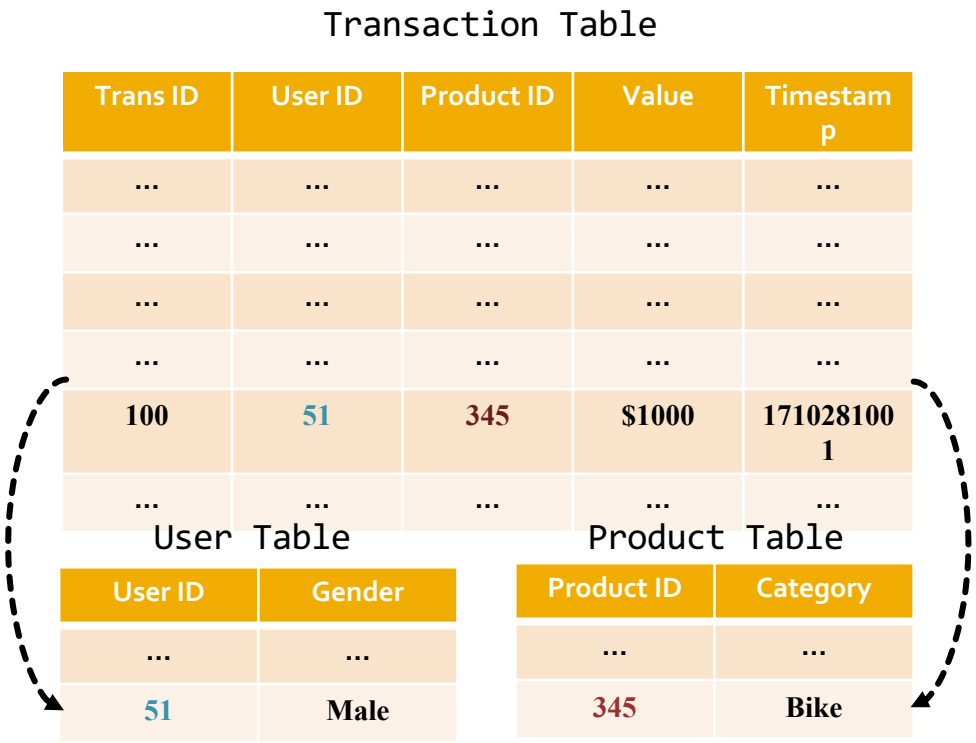
Create connections via primary-foreign keys



# Mathematically...

- Given database of tables $\mathcal{T} = \{T_1, \ldots, T_n\}$ and relations $\mathcal{L} \subseteq \mathcal{T} \times \mathcal{T}$
- Each table is a set of entities $v \in T_i$ possessing a primary key and optional foreign keys
- The **relational entity graph** is such that
  - the set of nodes is defined by all rows in all tables $$\mathcal{V} = \bigcup_{T \in \mathcal{T}} T$$
  - The set of edges is defined by connecting two entities $v_1, v_2$ whose primary and foreign keys match

# Entities in Relational Entity Graph




- Entities also have features (different than KGs)

# Stanford CS224W: Predictive Tasks in Relational Databases

CS224W: Machine Learning with Graphs

Jure Leskovec, Stanford University

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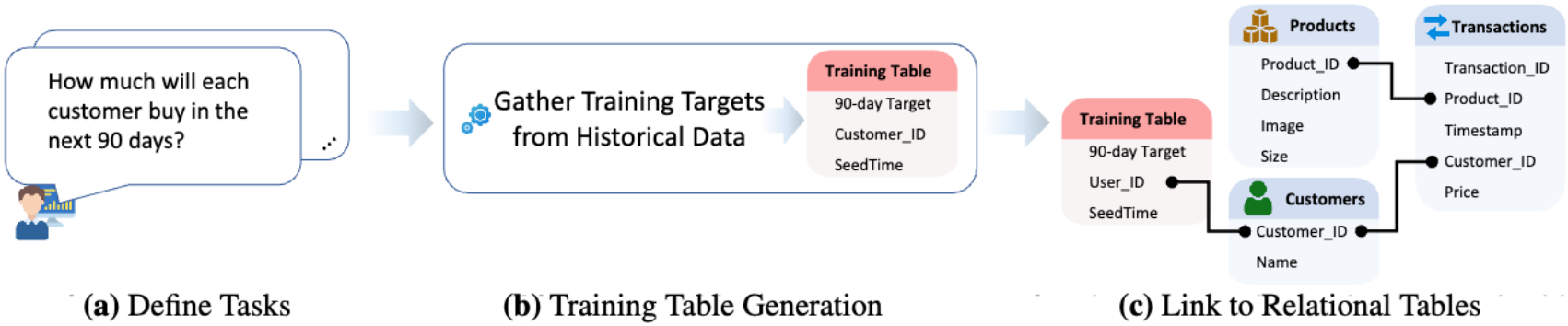
# Overview of the Approach

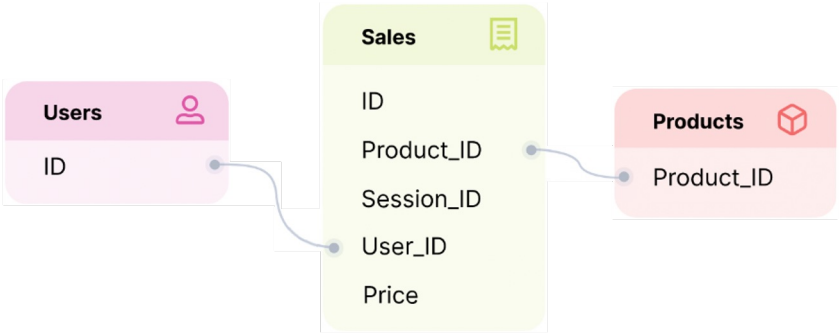



**(a)** Define Tasks **(b)** Training Table Generation **(c)** Link to Relational Tables

- Next:
  - Define task(s)
  - Relational Deep Learning

# Defining a Task

- **Example:** Predict whether a user is going to churn in the next 30 days?
- Most tasks are **temporal**:
  - Customer's label changes over time
  - Database changes over time
    - For every time, a feature needs to be recomputed
- To define a task, we need:
  - Entity
  - Label
  - Time




Temporal tasks as especially challenging because features are time dependent:

- For every time, a feature needs to be recomputed
- Entity's label can change between time steps

# Defining a Task: Training Table

- Training Table: A special table containing training labels
  - (entity ID, time, labels)
    - Classification, Regression, Multi-class
  - time column is essential for temporal prediction tasks
    - An entity may have different labels at different times
    - Only use information up to the time of label

# Defining a Task: Training Table

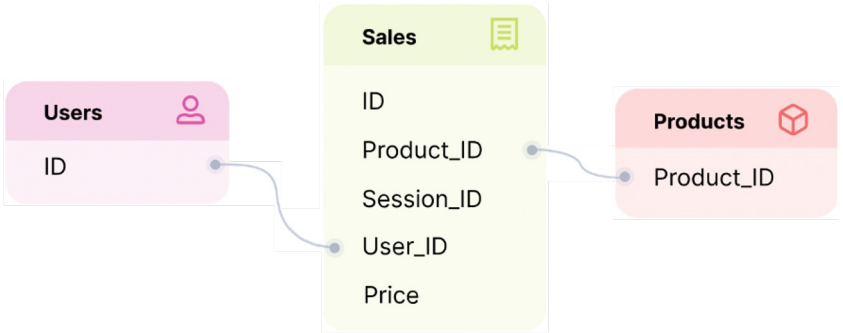
- Training Table: A special table containing training labels
  - (entity ID, time, labels)
    - Classification, Regression, Multi-class

Training Table

| Entity ID | Timestamp | Label |
|---|---|---|
| 99 | 10172024 | 1 |
| 99 | 10182024 | 1 |
| … | … | … |
| 100 | 10172024 | 1 |
| 100 | 10182024 | 0 |
| … | … | … |

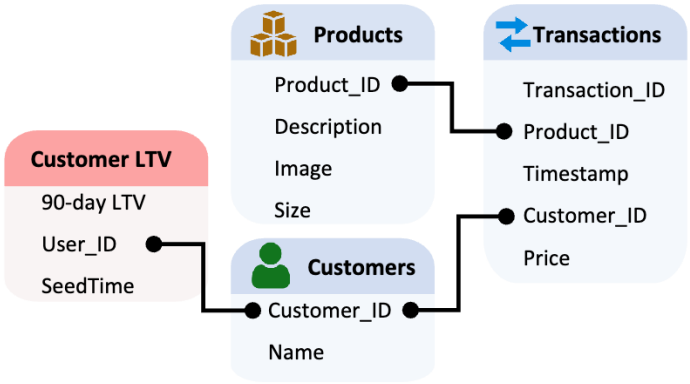
# Example: Churn

- Schema:

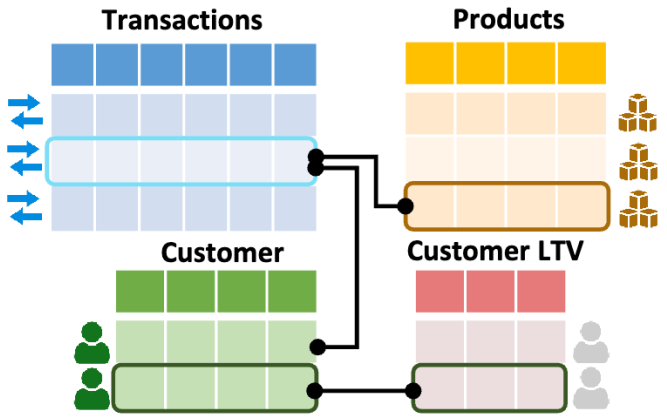



- Example prediction task:
  - Predict whether a user is going to churn
    - Zero sales in the next 30 days.
- Training table:
  - (user, time, churn label)

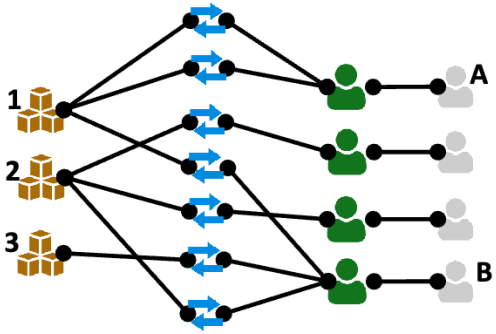
# Relational Deep Learning



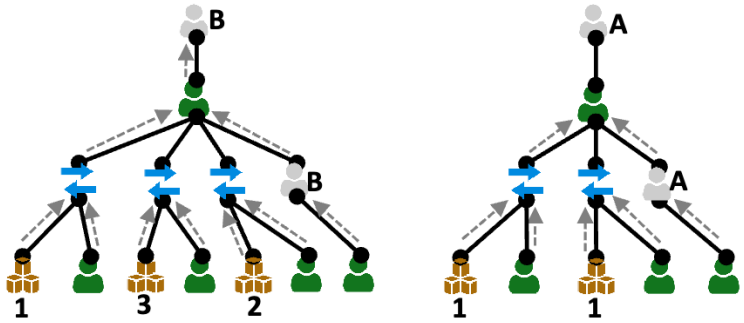

(a) Rel. Tables with Training Table




(b) Entities Linked by Foreign Keys




(c) Relational Entity Graph

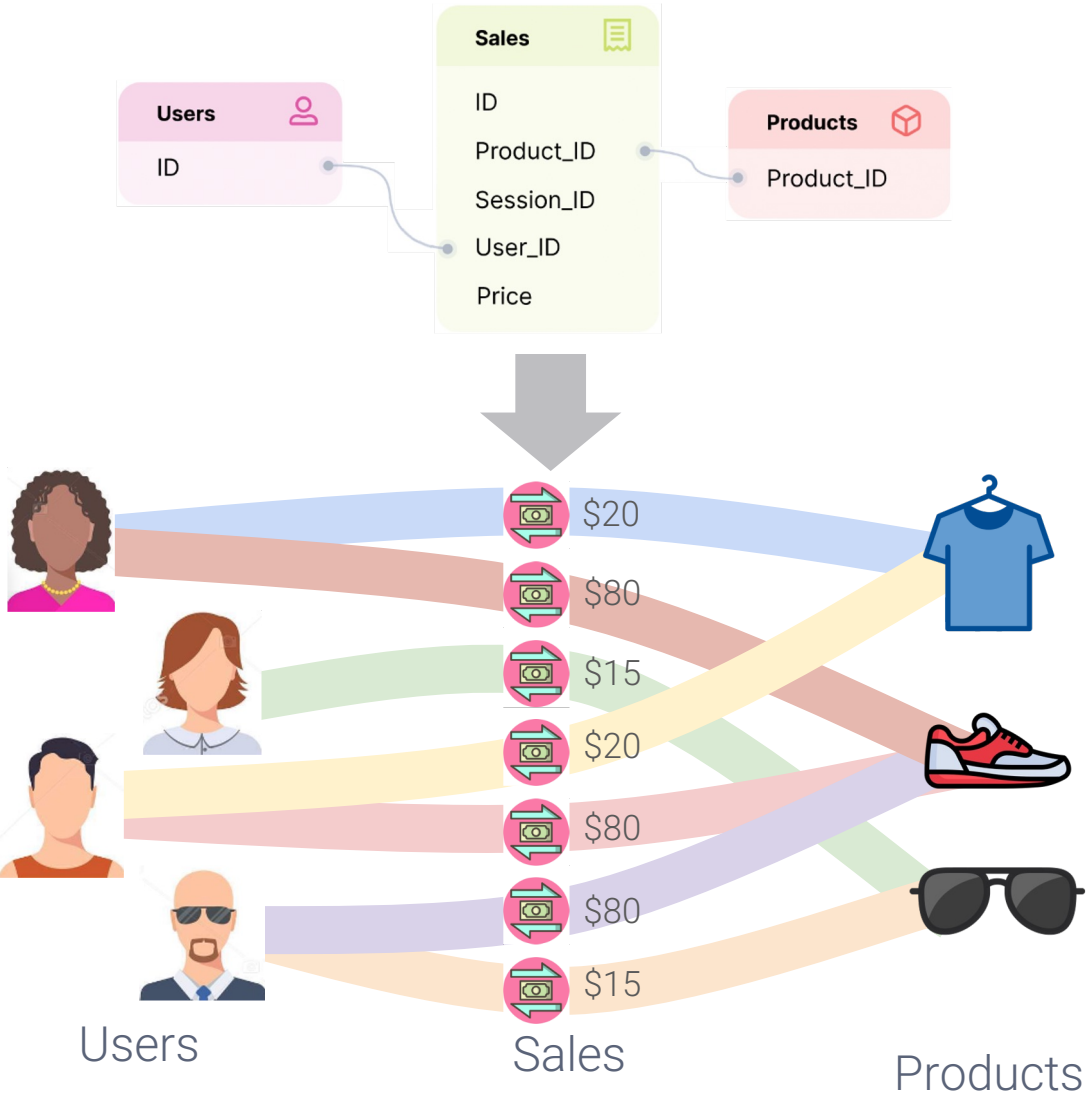



(d) Graph Neural Network

# Relational Entity Graph

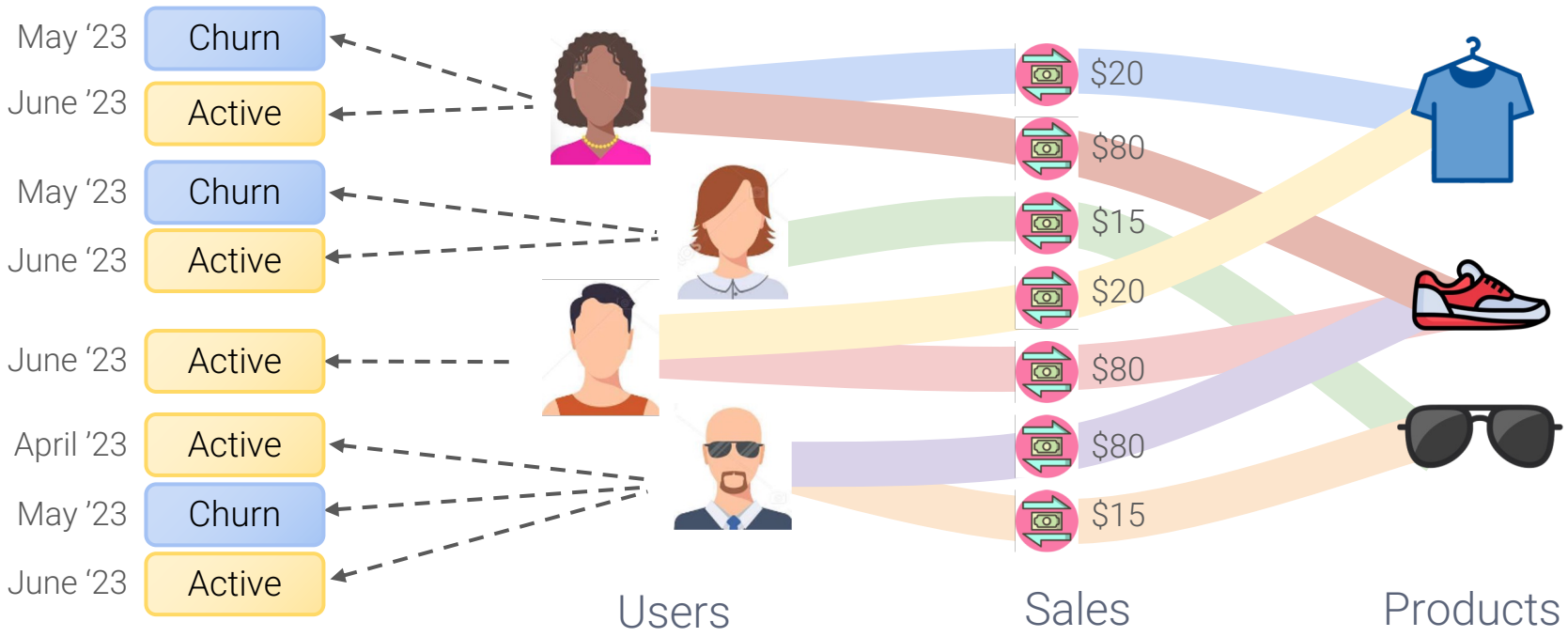
**Relational Entity Graph:**

Create connections via primary-foreign keys



# Connect the Training Table

Training labels together with timestamps are attached to the graph



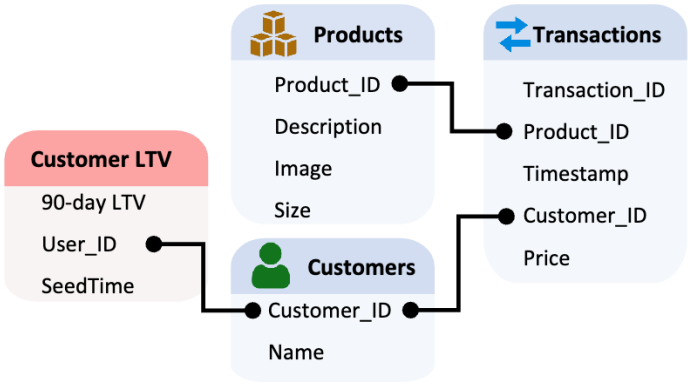
# Stanford CS224W: Relational GNN

CS224W: Machine Learning with Graphs

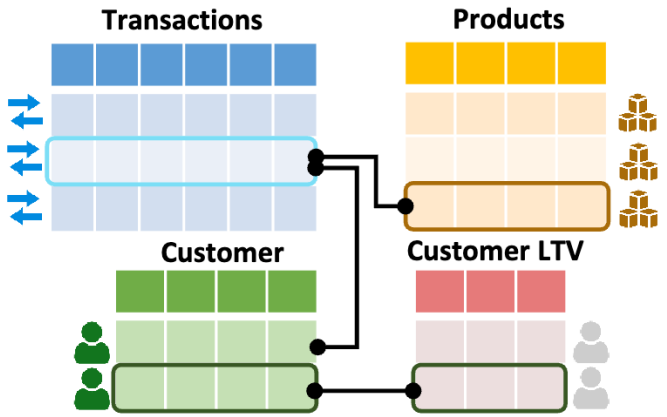
Jure Leskovec, Stanford University

http://cs224w.stanford.edu

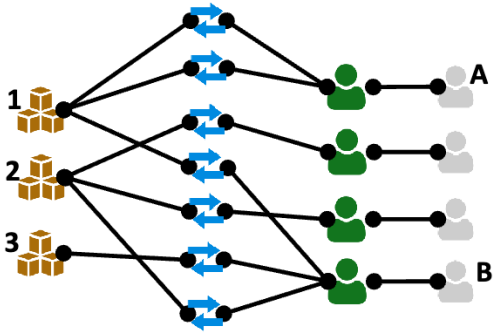
# Relational Deep Learning



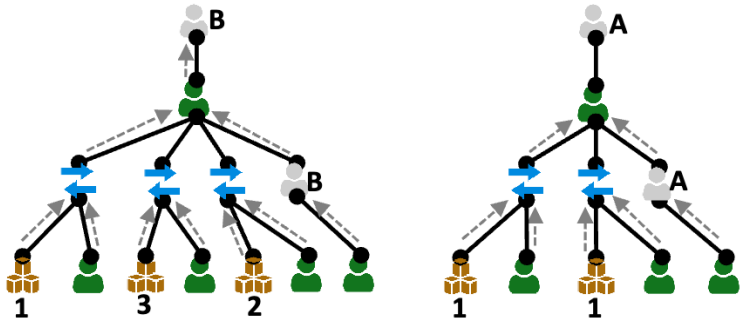

(a) Rel. Tables with Training Table




(b) Entities Linked by Foreign Keys




(c) Relational Entity Graph

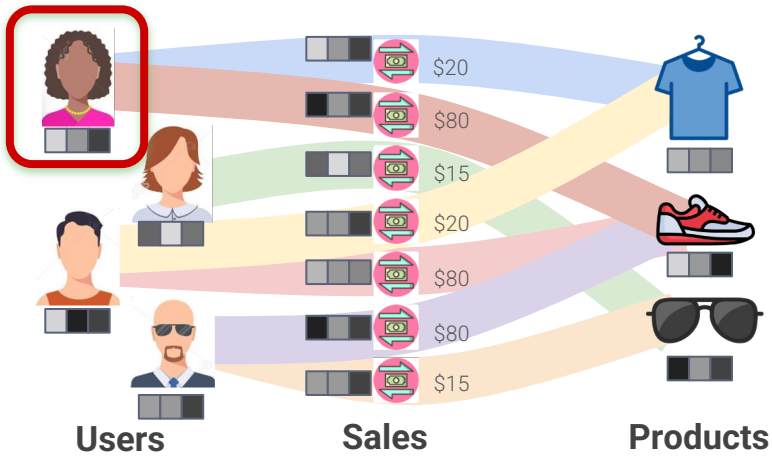



(d) Graph Neural Network

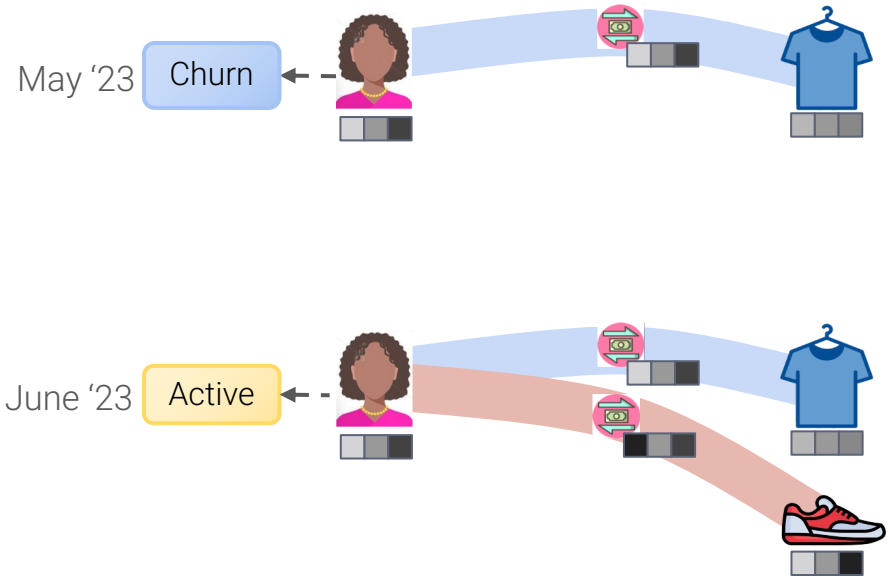
# GNN on the Entity Graph

## Node's neighborhood defines a computation graph

Nodes learn how to *optimally* use information from neighbors to obtain enhanced node representations

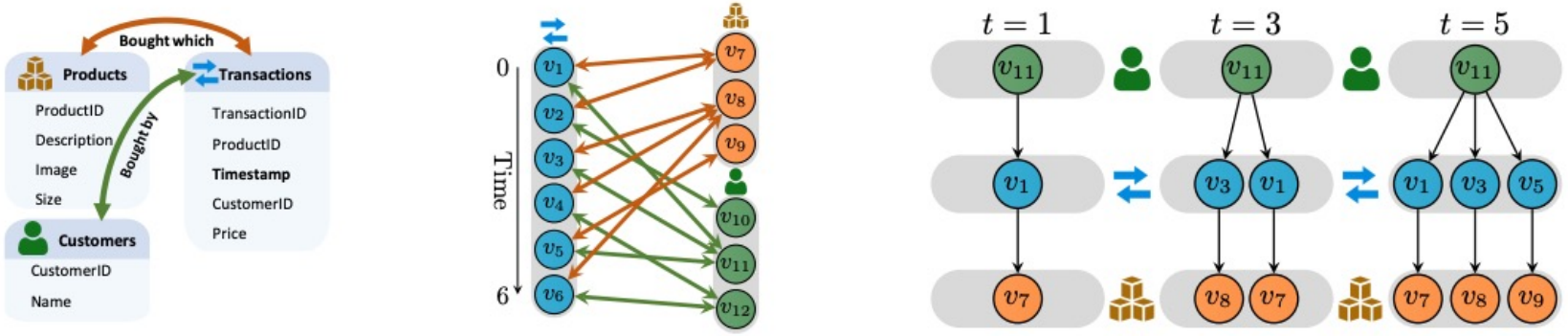



Entity Graph




GNN computation graphs

# GNNs on Temporal Graphs

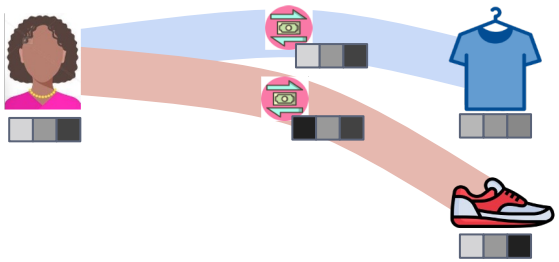



(a) Schema Graph (b) Relational Entity Graph (c) Computation Graphs for different time $t$

- The computation graph for each node is **time-dependent**
- Message+Aggregation becomes **time-dependent**
- Sampling over neighbors is **time-dependent**

# GNN vs Feature Engineering

**GNN-based features:**



VS.

**Hand-engineered features:**

| | | |
|---|---|---|
| SUM(TRANSACTIONS.Price) over (-30, 0) days | AVG(TRANSACTIONS.Price) over (-30, 0) days | ... |

GNN aggregation is **learnable version of hand-crafted features**!

GNNs give better performance by learning optimal features.

# SQL joins vs Graph edges

Definitions:

- A table $R$ is a set of entities $R = \{r_1, \ldots, r_n\}$
- Each entity is a tuple $r_i = (r_{i1}, r_{i2}, \ldots, r_{in})$
- Given two tables, $R, S$, a join operation is a subset of a Cartesian product:

- Aggregation will specify which rows are kept

Ex.1: Cross Join

**Employee table**

| LastName | DepartmentID |
|---|---|
| Rafferty | 31 |
| Jones | 33 |
| Heisenberg | 33 |
| Robinson | 34 |
| Smith | 34 |
| Williams | NULL |

**Department table**

| DepartmentID | DepartmentName |
|---|---|
| 31 | Sales |
| 33 | Engineering |
| 34 | Clerical |
| 35 | Marketing |

```
SELECT *
FROM employee INNER JOIN department ON 1=1;
```

| Employee.LastName | Employee.DepartmentID | Department.DepartmentName | Department.DepartmentID |
|---|---|---|---|
| Rafferty | 31 | Sales | 31 |
| Jones | 33 | Sales | 31 |
| Heisenberg | 33 | Sales | 31 |
| Smith | 34 | Sales | 31 |
| Robinson | 34 | Sales | 31 |
| Williams | NULL | Sales | 31 |
| Rafferty | 31 | Engineering | 33 |
| Jones | 33 | Engineering | 33 |
| Heisenberg | 33 | Engineering | 33 |
| Smith | 34 | Engineering | 33 |
| Robinson | 34 | Engineering | 33 |
| Williams | NULL | Engineering | 33 |
| Rafferty | 31 | Clerical | 34 |
| Jones | 33 | Clerical | 34 |
| Heisenberg | 33 | Clerical | 34 |
| Smith | 34 | Clerical | 34 |
| Robinson | 34 | Clerical | 34 |
| Williams | NULL | Clerical | 34 |
| Rafferty | 31 | Marketing | 35 |
| Jones | 33 | Marketing | 35 |
| Heisenberg | 33 | Marketing | 35 |
| Smith | 34 | Marketing | 35 |
| Robinson | 34 | Marketing | 35 |
| Williams | NULL | Marketing | 35 |

https://en.wikipedia.org/wiki/Relational_algebra

# SQL joins vs Graph edges

## Connection between SQL Joins and graph edges

Ex.2: Inner Join

$$R \bowtie S := \{r \cup s | r \in R \wedge s \in S \wedge \mathrm{Fun}(r,s)\}$$

$$\mathrm{Fun}(r,s): r.pkey = s.fkey$$

**Employee table**

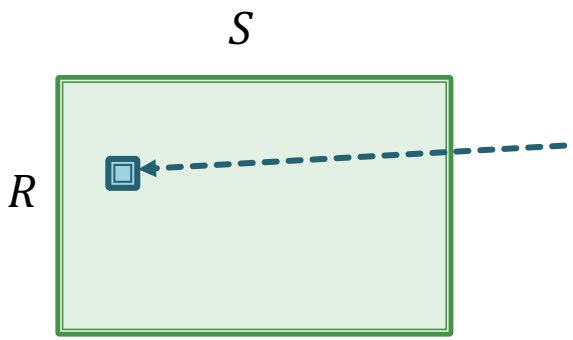
| LastName | DepartmentID |
|---|---|
| Rafferty | 31 |
| Jones | 33 |
| Heisenberg | 33 |
| Robinson | 34 |
| Smith | 34 |
| Williams | NULL |

**Department table**

| DepartmentID | DepartmentName |
|---|---|
| 31 | Sales |
| 33 | Engineering |
| 34 | Clerical |
| 35 | Marketing |

```
SELECT employee.LastName, employee.DepartmentID, department.DepartmentName
FROM employee
INNER JOIN department ON
employee.DepartmentID = department.DepartmentID;
```

| Employee.LastName | Employee.DepartmentID | Department.DepartmentName |
|---|---|---|
| Robinson | 34 | Clerical |
| Jones | 33 | Engineering |
| Smith | 34 | Clerical |
| Heisenberg | 33 | Engineering |
| Rafferty | 31 | Sales |




These are exactly the pkey-fkey edges!

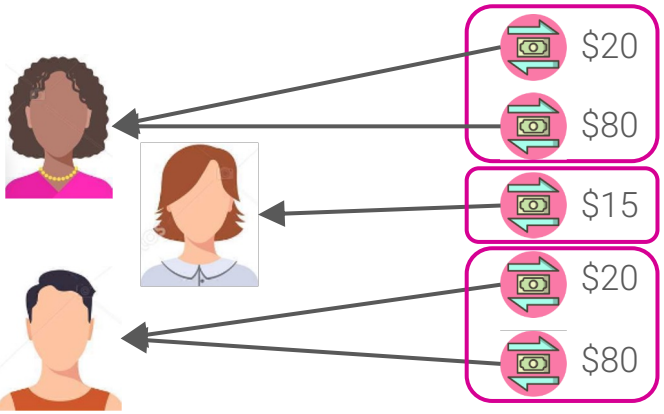
https://en.wikipedia.org/wiki/Relational_algebra

# GNNs perform a JOIN+AGG

Input:

| USER_ID |
|---|
| 1 |
| 2 |
| 3 |

| USER_ID | VALUE | DATE |
|---|---|---|
| 1 | 20 | 01-01 |
| 1 | 80 | 01-02 |
| 2 | 15 | 01-01 |
| 3 | 20 | 01-02 |
| 3 | 80 | 01-03 |




$$\bigoplus_{w \in \mathcal{N}(v)} \mathbf{t}(t_w) \cdot \mathbf{x}_w$$

GNN can learn:

```
SELECT SUM(VALUE)
FROM SALES
WHERE DATE > 01-01
GROUP BY USER_ID
```

| USER_ID | SUM(VALUE) |
|---|---|
| 1 | 80 |
| 2 | 0 |
| 3 | 100 |

Learnable Aggregation $\bigoplus$

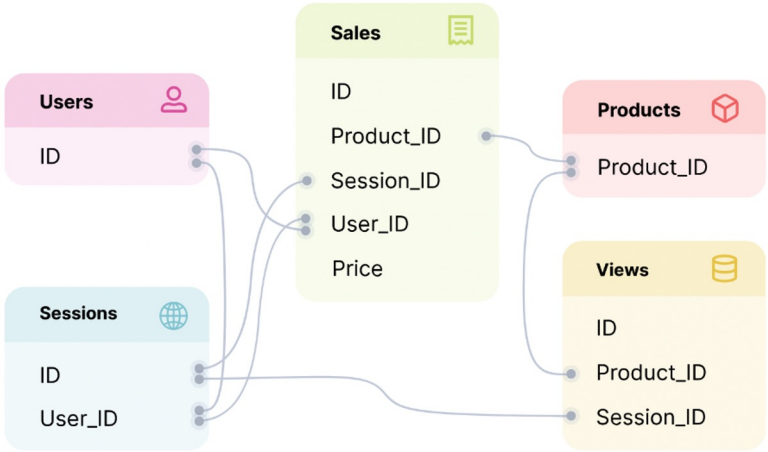
Temporal embedding $\mathbf{t}(t_w)$

Fact representation $\mathbf{x}_w$

# Benefits of GNNs

GNNs learn how to aggregate information:

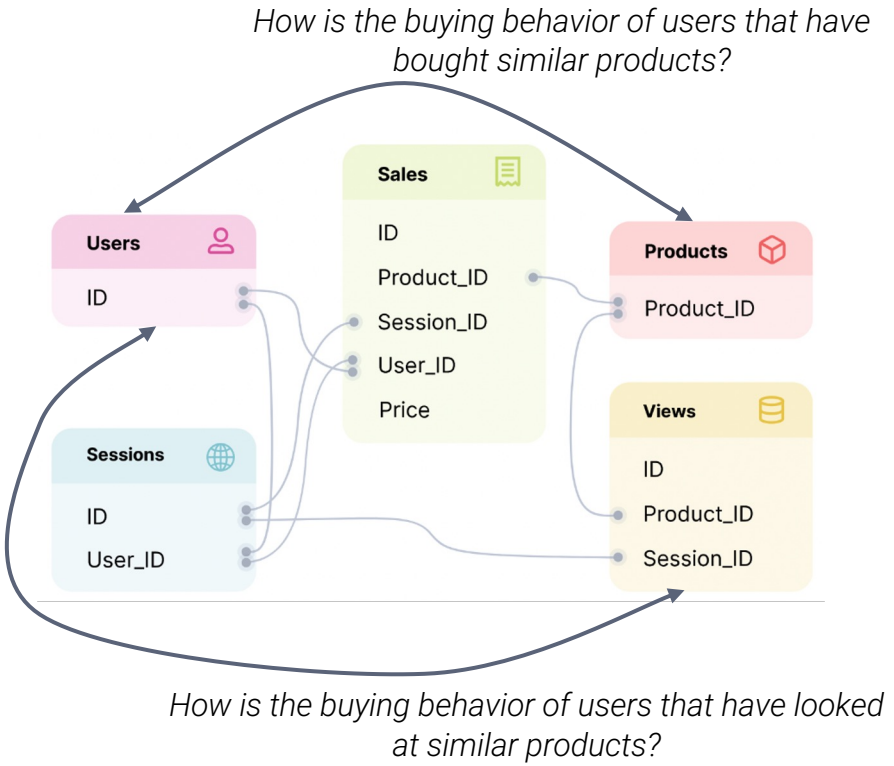
- They can discard neighboring node information that is irrelevant for the given downstream task
- They can detect fine-grained patterns within local neighborhoods (e.g., buying behavior over the last year)



# Benefits of GNNs

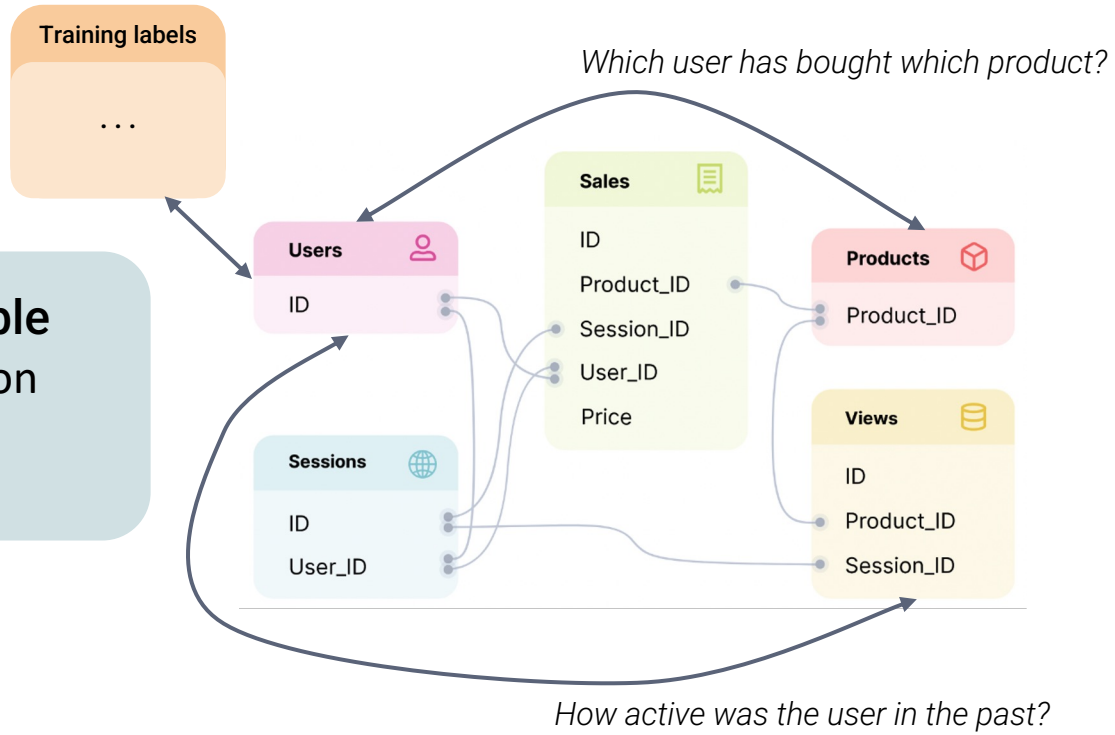
## GNNs can exchange information *across* training examples:

- Instead of treating examples as isolated, there now exists an inter-dependency *between* entities (*e.g.*, users with similar features, users with similar behavior)
- GNN can *use* these features to enrich an entity's representation



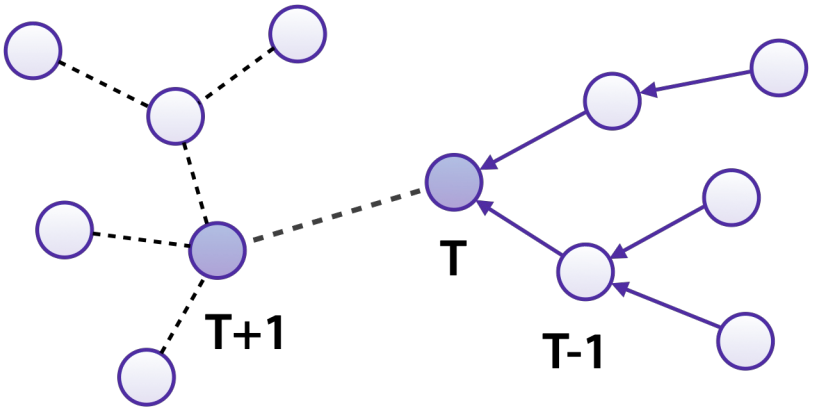
# Benefits of GNNs

**Multi-hop reasoning** *across* **table boundaries** can catch information which is **hard** to pre-compute *beforehand*



# Benefits of GNNs

- First-class temporal support
  - Capture fine-grained relative and seasonal features via temporal embeddings
  - Avoid data leakage via temporal sampling directly during data loading



# Full Vision Described in Paper

**Relational Deep Learning: Graph Representation Learning on Relational Tables**

**Matthias Fey**[2,*], **Weihua Hu**[2,*], **Kexin Huang**[1,*], **Jan Eric Lenssen**[2,3,*], **Rishabh Ranjan**[1,*], **Joshua Robinson**[1,*], **Rex Ying**[4], **Jiaxuan You**[5], **Jure Leskovec**[1,2]

[*]Equal contribution. Listed in alphabetic order.

[1]Stanford University
[2]Kumo.AI
[3]Max Planck Institute for Informatics
[4]Yale University
[5]University of Illinois at Urbana-Champaign

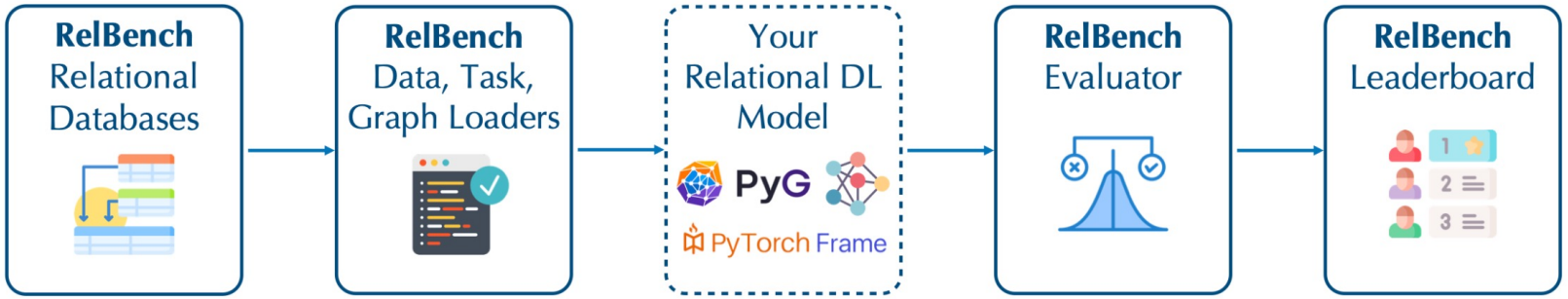
Available at: https://relbench.stanford.edu


# Stanford CS224W: RELBENCH

CS224W: Machine Learning with Graphs
Jure Leskovec, Stanford University
http://cs224w.stanford.edu

# Enabling Research on RDL

- Relbench is more than just a collection of Databases




- Automatically download datasets
- Load database and task tables
- Standardized evaluation protocol:
  - Prevents temporal leakage from test set
- Framework-agnostic data structures: use your favorite ML stack!

# PyF and PyG Integration

- Load as a PyG graph
- Train GNN end-to-end
- Temporal neighbor sampling
- Use PyTorch Frame to encode tables


# RelBench Datasets

## 7 Diverse Datasets

**E-Commerce**

- rel-amazon
- rel-avito
- rel-hm

**Social**

- rel-event
- rel-stack

**Sports**

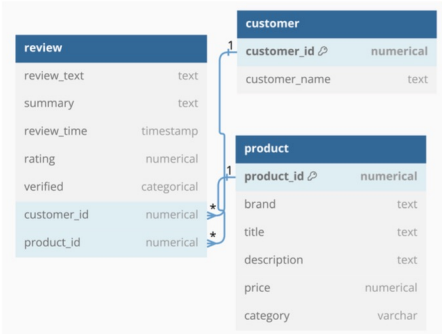
- rel-f1

**Medical**

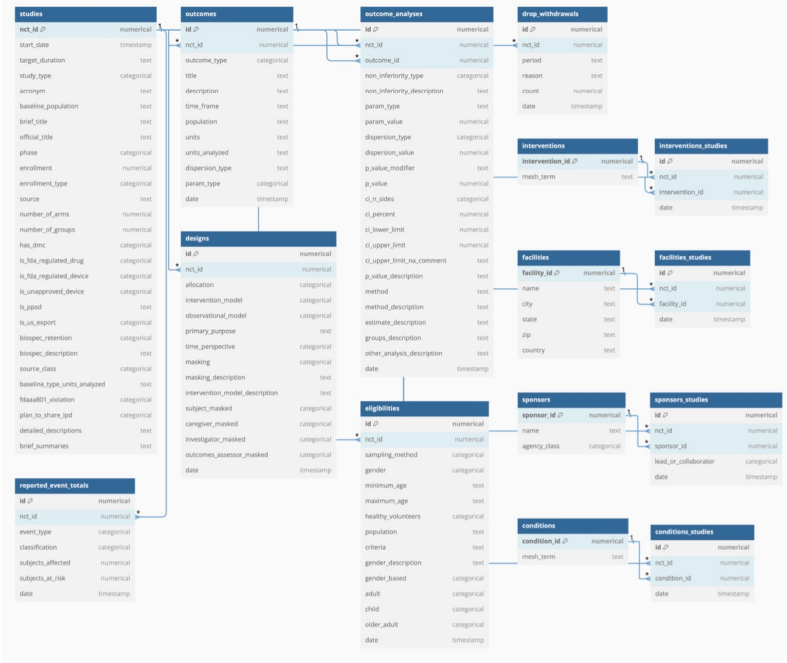
- rel-trial

# RelBench Datasets

## Rich Schemas




rel-amazon




rel-trial

**3** to **15** tables

**74k** to **41M** rows in a DB

**15** to **140** columns in a DB

Time span from **2 weeks** to **55 years**

# RelBench Tasks

## 30 Real-World Predictive Tasks

**Entity Classification**

- rel-amazon
  - user-churn
  - item-churn
- rel-stack
  - user-badge
- rel-trial
  - study-outcome

…

**Entity Regression**

- rel-amazon
  - user-ltv
  - item-ltv
- rel-avito
  - ad-ctr
- rel-f1
  - driver-position

…

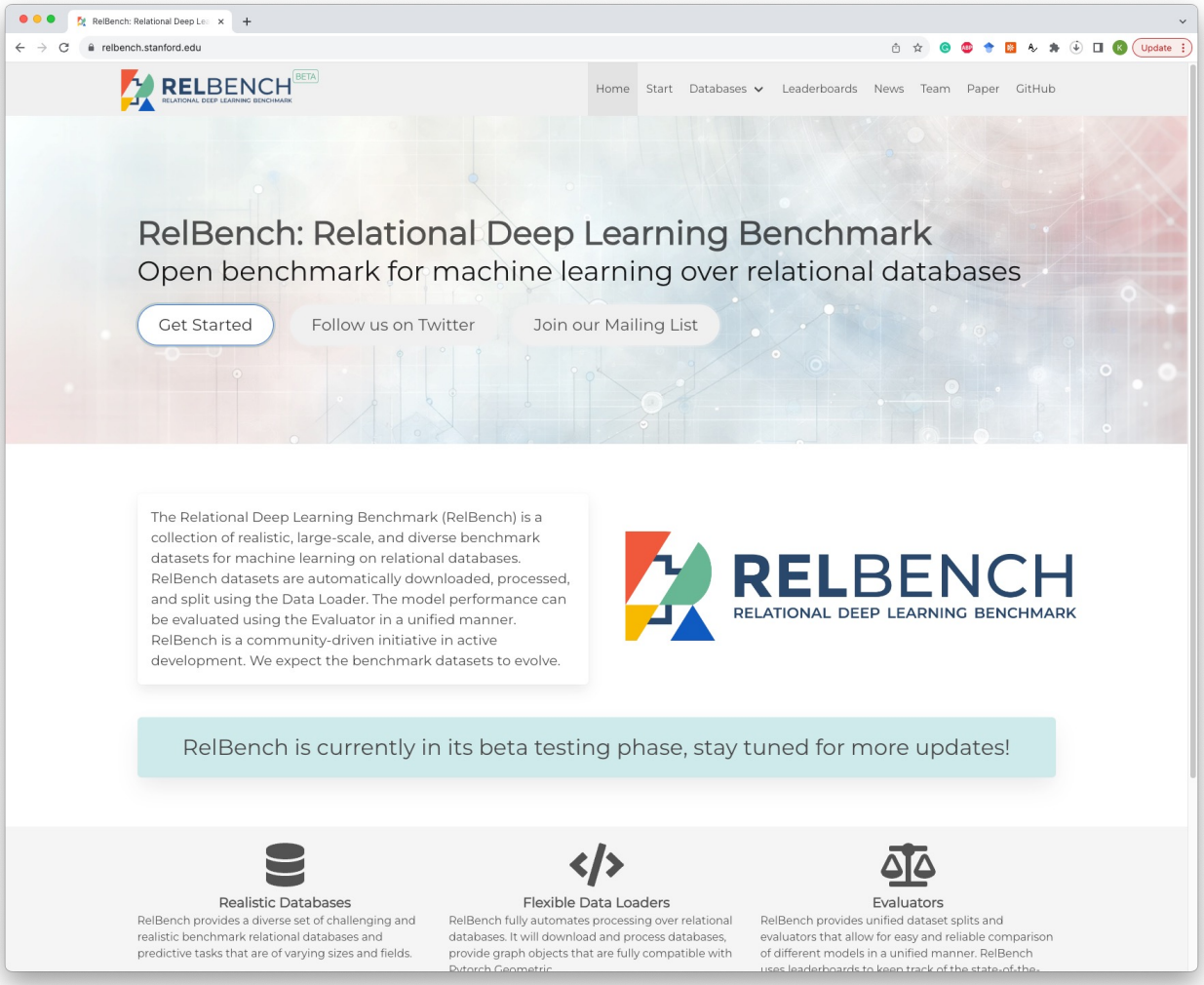
**Recommendation**

- rel-amazon
  - user-item-purchase
- rel-avito
  - user-ad-visit
- rel-stack
  - user-post-comment
  - post-post-related

…

# See website to get started

https://relbench.stanford.edu



# Stanford CS224W: GNN vs expert Data Scientist

CS224W: Machine Learning with Graphs
Jure Leskovec, Stanford University
http://cs224w.stanford.edu

# Expert Data Scientist

*(Alejandro)*

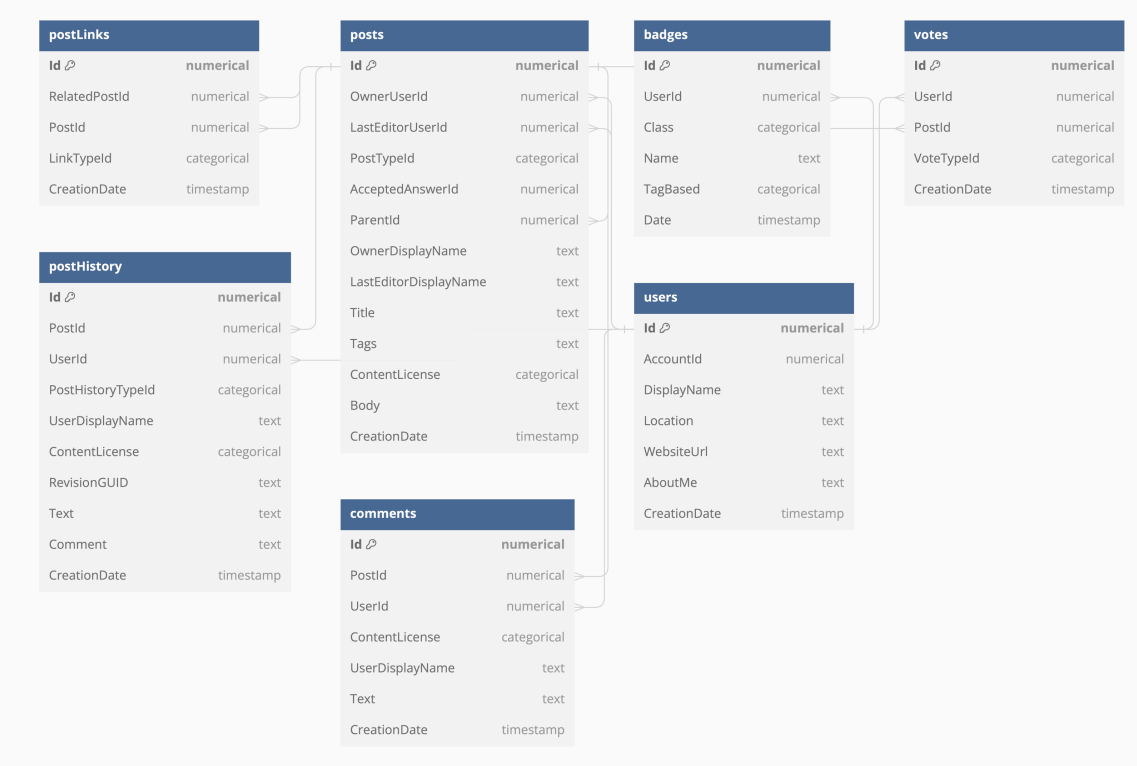
- Recruited Experienced Data Scientist
- 5 years in industry *(specializing in financial databases)*
- Responsible for full model building lifecycle *(more detail next)*


RELBENCH
RELATIONAL DEEP LEARNING BENCHMARK

# Representative Relbench task

Q: Will a user be active in the next 6 months?

Stack Exchange Database



# Expert Data Scientist Workflow

Task: Will a user be active in the next 6 months?

# Expert Data Scientist Workflow

Manual work

Task: Will a user be active in the next 6 months?

Exploratory Data Analysis (EDA)

4hrs

# Expert Data Scientist Workflow

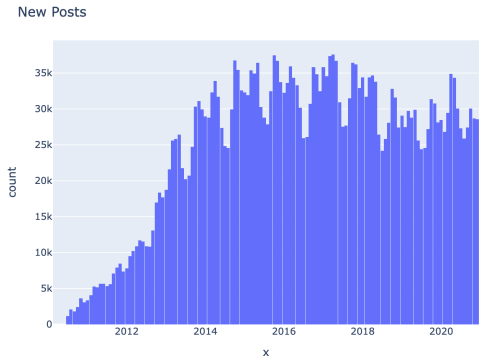
Manual work

Task: Will a user be active in the next 6 months?

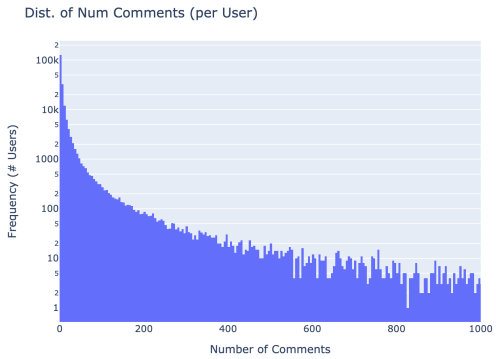
Exploratory Data Analysis (EDA)

4hrs

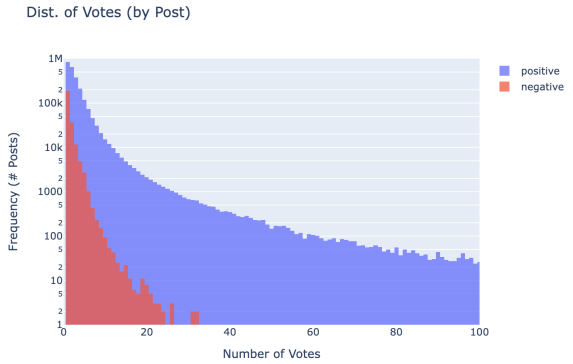
*Example observations*




Activity is seasonal




Comments follow power law




Negative votes are infrequent

# Expert Data Scientist Workflow

Manual work

Task: Will a user be active in the next 6 months?

Exploratory Data Analysis (EDA) — 4hrs

↓

Feature Ideation — 0.5hr

*Example features*

- ✓ weeks_since_last_comment
- ✓ badge_score
- ✓ location_is_null

# Expert Data Scientist Workflow

Manual work

Exploratory Data Analysis (EDA) — 4hrs

↓

Feature Ideation — 0.5hr

↓

SQL query writing — 5hr

*Example features*

- ✓ weeks_since_last_comment
- ✓ badge_score
- ✓ location_is_null

Task: Will a user be active in the next 6 months?

```sql
create table churn_feats_train as

with labels as (
    select * from train_labels
),

badge_freqs as (
    select
        Name,
        count(*) / (sum(count(*)) over ()) as badge_incidence
    from badges
    group by Name
),

badge_feats as (
    select
        labels.OwnerUserId as user_id,
        labels.timestamp,
        coalesce(count(distinct badges.Id), 0) as num_badges,
        coalesce(sum(log(1 / badge_freqs.badge_incidence)), 0) as badge_score
    from labels
    left join badges
        on
            labels.OwnerUserId = badges.UserId
            and labels.timestamp > badges.Date
    left join badge_freqs
        on badges.Name = badge_freqs.Name
    group by all
),

user_feats as (
```

100s of lines of code

# Expert Data Scientist Workflow

Manual work

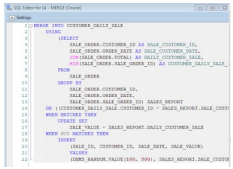
Task: Will a user be active in the next 6 months?

Exploratory Data Analysis (EDA) — 4hrs

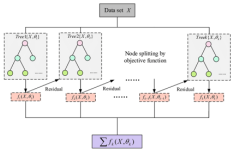
*Example features*

- ✓ weeks_since_last_comment
- ✓ badge_score
- ✓ location_is_null

Feature Ideation — 0.5hr



SQL query writing — 5hr



XGBoost hparam sweep — 2hr

# Expert Data Scientist Workflow

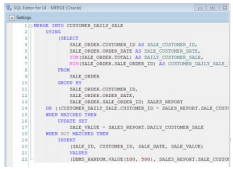
Manual work

Task: Will a user be active in the next 6 months?

Exploratory Data Analysis (EDA) — 4hrs

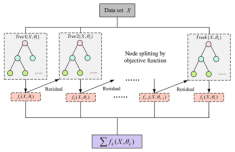
*Example features*

- ✓ weeks_since_last_comment
- ✓ badge_score
- ✓ location_is_null



Feature Ideation — 0.5hr

SQL query writing — 5hr



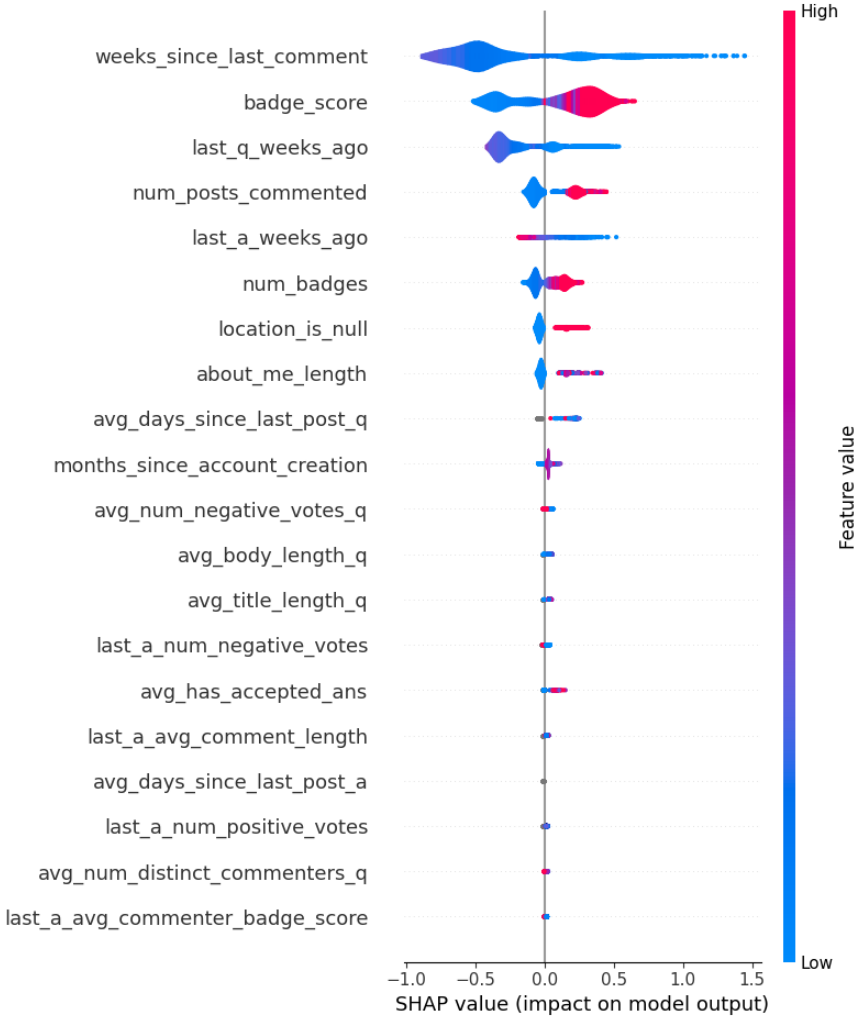

XGBoost hparam sweep — 2hr

SHAP (feature importance analysis) — 1hr

# SHAP feature importance analysis

*Selected Observations*

- *Website "seniority" **predictive** (total number of comments, badge score etc.)*
- *Time since last active / commented **is predictive***
- *Completed bio (about me, location etc.) **is predictive***
- *Number of positive/negative votes **not predictive***
- *Interacting with "senior" community members **not predictive***



# Final list of features

*~12 hours of high-quality expert work*

[2]:

| | Label Corr. | Label MI | NaN % |
|---|---|---|---|
| num_badges | 0.229 | 0.057 | 0.0% |
| num_questions_last_6mo | 0.209 | 0.067 | 89.7% |
| badge_score | 0.206 | 0.069 | 0.0% |
| ans_acceptance_rate | 0.195 | 0.094 | 96.4% |
| avg_comment_length | 0.135 | 0.045 | 0.0% |
| num_posts_commented | 0.131 | 0.061 | 0.0% |
| avg_num_tags | 0.131 | 0.077 | 89.7% |
| avg_has_accepted_ans | 0.130 | 0.106 | 89.7% |
| num_comments | 0.130 | 0.057 | 0.0% |
| num_answers_last_6mo | 0.125 | 0.037 | 96.4% |
| last_q_num_tags | 0.111 | 0.014 | 13.6% |
| avg_num_positive_votes_a | 0.108 | 0.070 | 96.4% |
| last_a_is_accepted_ans | 0.106 | 0.049 | 73.3% |
| last_q_body_length | 0.096 | 0.007 | 13.6% |
| about_me_length | 0.096 | 0.010 | 0.0% |
| avg_num_comments_a | 0.084 | 0.088 | 96.4% |
| last_q_has_accepted_ans | 0.076 | 0.009 | 13.6% |
| avg_num_distinct_commenters_a | 0.073 | 0.073 | 96.4% |
| avg_body_length_q | 0.067 | 0.051 | 89.7% |
| avg_num_positive_votes_q | 0.060 | 0.078 | 89.7% |
| last_a_body_length | 0.056 | 0.023 | 73.3% |
| avg_body_length_a | 0.034 | 0.033 | 96.4% |
| last_q_title_length | 0.023 | 0.004 | 13.6% |
| last_a_num_comments | 0.023 | 0.040 | 73.3% |
| last_q_num_comments | 0.015 | 0.003 | 13.6% |
| avg_avg_comment_length_a | 0.012 | 0.047 | 96.4% |
| last_q_avg_comment_length | 0.009 | 0.001 | 13.6% |
| display_name_is_null | 0.004 | 0.001 | 0.0% |
| last_a_num_distinct_commenters | 0.002 | 0.057 | 73.3% |
| last_q_num_distinct_commenters | -0.002 | 0.006 | 13.6% |
| last_q_num_positive_votes | -0.006 | 0.002 | 13.6% |
| last_a_num_positive_votes | -0.009 | 0.030 | 73.3% |
| last_a_avg_comment_length | -0.010 | 0.022 | 73.3% |
| avg_num_comments_q | -0.011 | 0.078 | 89.7% |
| avg_commenter_badge_score_q | -0.015 | 0.048 | 89.7% |
| avg_title_length_q | -0.022 | 0.064 | 89.7% |
| last_q_num_negative_votes | -0.026 | 0.002 | 13.6% |
| avg_num_distinct_commenters_q | -0.037 | 0.096 | 89.7% |
| avg_avg_comment_length_q | -0.043 | 0.057 | 89.7% |
| last_q_avg_commenter_badge_score | -0.046 | 0.006 | 13.6% |
| last_a_avg_commenter_badge_score | -0.048 | 0.023 | 73.3% |
| avg_commenter_badge_score_a | -0.060 | 0.032 | 96.4% |
| website_url_is_null | -0.061 | 0.032 | 0.0% |
| last_a_num_negative_votes | -0.085 | 0.051 | 73.3% |
| months_since_account_creation | -0.113 | 0.011 | 0.0% |
| avg_num_negative_votes_q | -0.114 | 0.100 | 89.7% |
| location_is_null | -0.136 | 0.051 | 0.0% |
| avg_days_since_last_post_a | -0.168 | 0.035 | 97.1% |
| avg_days_since_last_post_q | -0.169 | 0.055 | 93.5% |
| avg_num_negative_votes_a | -0.170 | 0.088 | 96.4% |
| last_q_weeks_ago | -0.346 | 0.073 | 13.6% |
| weeks_since_last_comment | -0.392 | 0.091 | 34.3% |
| last_a_weeks_ago | -0.394 | 0.049 | 73.3% |
| last_a_num_tags | nan | 0.065 | 73.3% |

# Stanford CS224W: Results

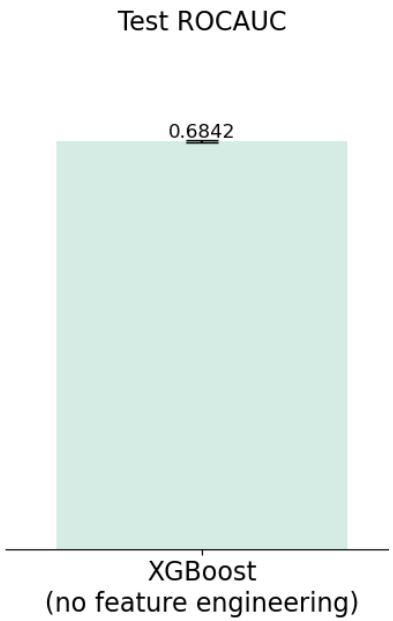
CS224W: Machine Learning with Graphs
Jure Leskovec, Stanford University
http://cs224w.stanford.edu

# Results

Task: Will a user be active in the next 6 months?

| users | |
|---|---|
| Id | numerical |
| AccountId | numerical |
| DisplayName | text |
| Location | text |
| WebsiteUrl | text |
| AboutMe | text |
| CreationDate | timestamp |

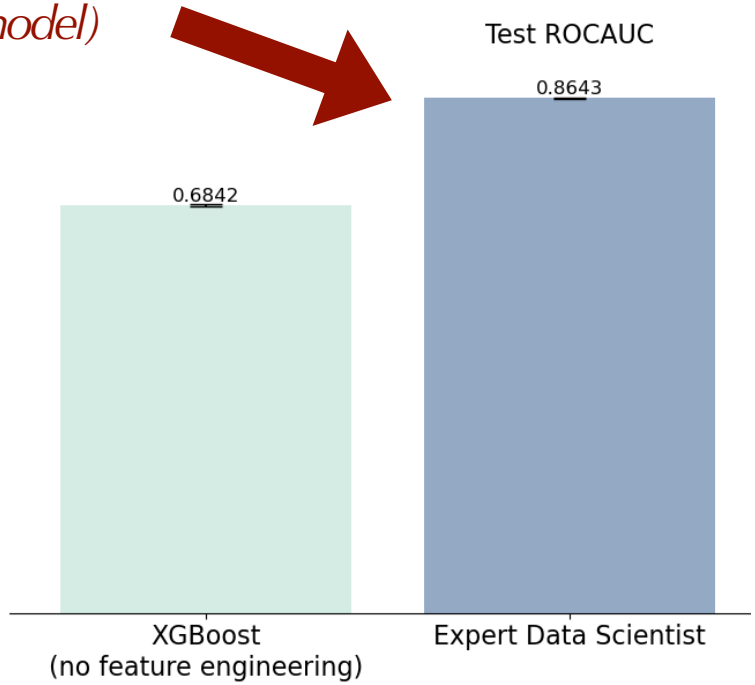
*Naive baseline*



# Results

**12 hours manual work**
**~682 lines of code**
**1hr model training**

*(2 days to model)*




**Work measured as the marginal effort to solve a new task*

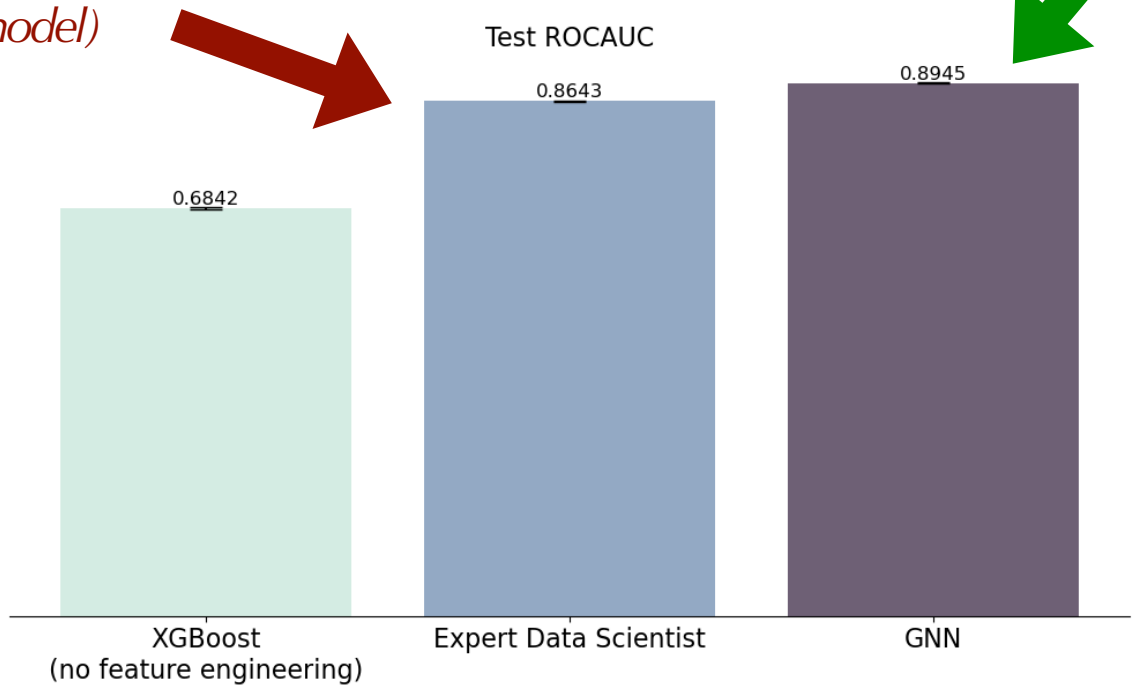
# Results

Task: Will a user be active in the next 6 months?

12 hours manual work
~682 lines of code
1hr model training

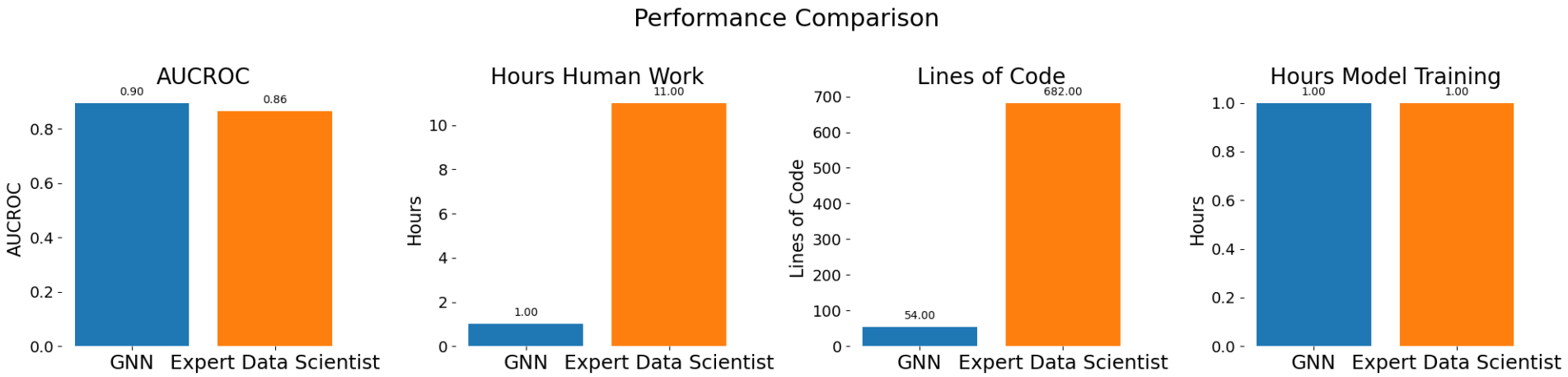
*(2 days to model)*

<1 hour manual work
54 lines of code
1hr model training



# Results

Task: Will a user be active in the next 6 months?



# More Relbench tasks