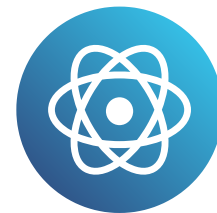


# Prediction vs. inference dilemma

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Head of Machine Learning & Science, AWS

# Inference vs. prediction dilemma

## Inference or causal models:

- The goal is to understand the drivers of a business outcome
- Inference focused models are interpretable
- Less accurate than **prediction** models

## Prediction:

- The prediction itself is the main goal
- Are not easily interpretable i.e. work like "black-boxes"
- Much more accurate than **inference** models

# Start with the business question

- "What are the main **drivers** of fraud?"
  - Inference
- "**How much** conditions X impact heart attack risk?"
  - Inference
- "**Which** transactions are **likely** fraudulent?"
  - Prediction
- "Is the patient **at risk** of having a heart attack?"
  - Prediction

# Modeling data structure

	Transaction data A	Transaction data B	Transaction data C	Transaction data D
Transaction 1				
Transaction 2				
Transaction 3				
Transaction ...				
Transaction N				

Fraud probability

# Target variable

	Transaction data A	Transaction data B	Transaction data C	Transaction data D
Transaction 1				
Transaction 2				
Transaction 3				
Transaction ...				
Transaction N				

## Target variable

Fraud probability

# Input features

**Data about transactions that the business collected  
(input features)**

	Transaction data A	Transaction data B	Transaction data C	Transaction data D
Transaction 1				
Transaction 2				
Transaction 3				
Transaction ...				
Transaction N				

**Target variable**

Fraud probability

# Using input features

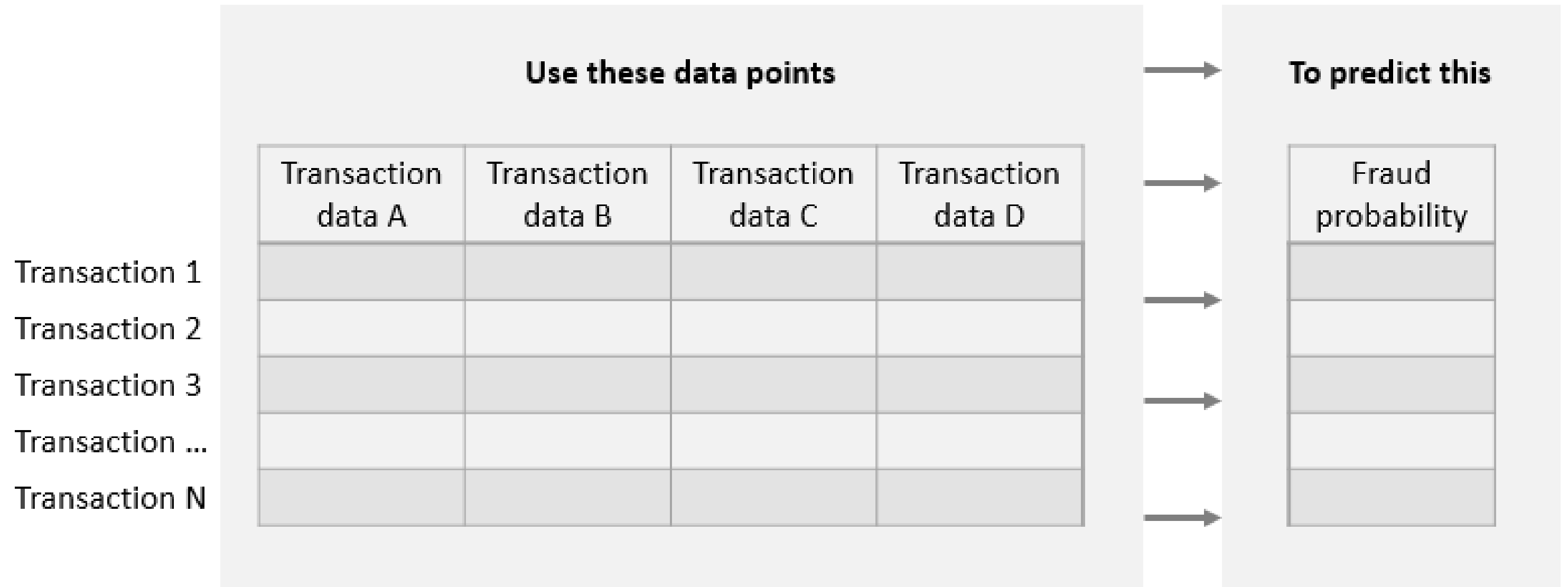
Transaction 1  
Transaction 2  
Transaction 3  
Transaction ...  
Transaction N

Use these data points

Transaction data A	Transaction data B	Transaction data C	Transaction data D

Fraud probability


# Predicting target variable





# Inference model focus

Which of these affect the fraud probability the most?

	Transaction data A	Transaction data B	Transaction data C	Transaction data D
Transaction 1				
Transaction 2				
Transaction 3				
Transaction ...				
Transaction N				

Fraud probability

# Prediction model focus

Transaction 1  
Transaction 2  
Transaction 3  
Transaction ...  
Transaction N

Transaction data A	Transaction data B	Transaction data C	Transaction data D

**Get the most  
accurate probability  
this is fraud**

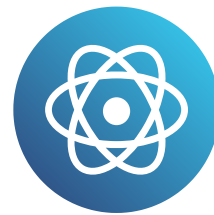
Fraud  
probability

# Let's practice!

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# Inference (causal) models

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Amazon

# What is causality?

- Identify causal relationship of how much certain actions affect an outcome of interest
- Answers the "why?" questions
- Optimizes for model interpretability vs. performance
- Models try to detect patterns in observed data (observational) and draw causal conclusions

# Experiments vs. observations

- Experiments are designed and causal conclusions are guaranteed e.g. in A/B tests
- When experiments are impossible (unethical, too expensive, both) - the models are used (also called observational studies) to calculate effect of certain inputs on desired outcomes
- Experiments are **always** preferred over observational studies whenever possible

# Best practices

1. Do experiments wherever you can
2. If running experiments all the time is too expensive, run them periodically (quarterly, annually) and use it as benchmark
3. If there are no way to run any experiments, build a causal model. This will require an advanced methodology

# Inference model example

	Last month spend	Recency in days	Average cart value	Store visits per year
Customer 1	845 USD	20	340 USD	32
Customer 2	205 USD	1	100 USD	25
Customer 3	0 USD	55	70 USD	14
Customer ...	...	...	...	...
Customer N	43	114.5	134	61.2

Next month spend
585 USD
150 USD
20 USD
...
69 USD



# Inference - training

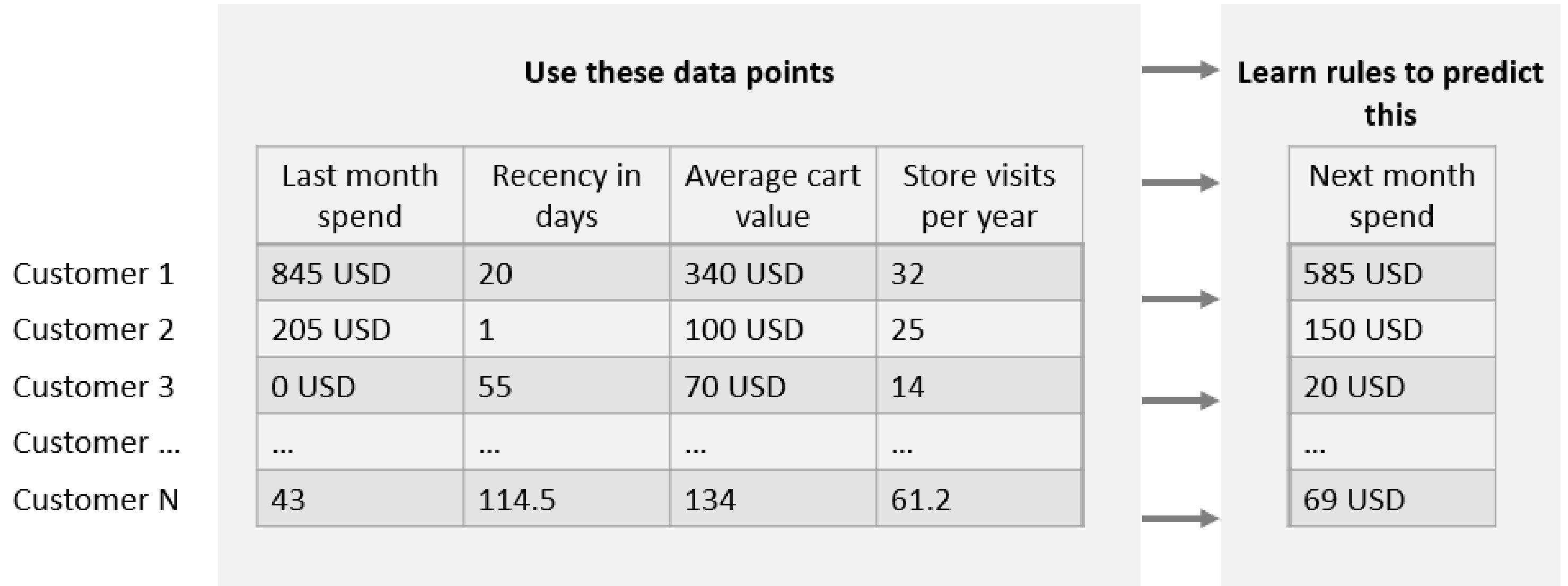
Customer 1  
Customer 2  
Customer 3  
Customer ...  
Customer N

## Use these data points

Last month spend	Recency in days	Average cart value	Store visits per year
845 USD	20	340 USD	32
205 USD	1	100 USD	25
0 USD	55	70 USD	14
...	...	...	...
43	114.5	134	61.2

Next month spend
585 USD
150 USD
20 USD
...
69 USD

# Inference - learning



# Inference - regression coefficients

**Coefficients**

Last month spend	Recency in days	Average cart value	Store visits per year
0.58	-0.03	0.28	0.18

# Inference - interpretation

**Coefficients**

Last month spend	Recency in days	Average cart value	Store visits per year
0.58	-0.03	0.28	0.18

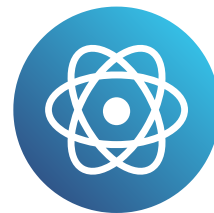
How much 1 incremental USD spent in the last month results in predicted next month spend.  
Here, the customers who on average spent 1 USD **more** in the last month, will spend 0.58 USD more in the next month compared to customers with 1 USD **less** last month.

# Let's practice!

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# Prediction models (supervised learning)

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Amazon

# Supervised vs. Unsupervised

## Supervised models

Predicting **class/type** of an outcome (e.g. subscription cancellation, fraud, purchase) -

**CLASSIFICATION**

Predicting **quantity** of an outcome (e.g. dollars spent, hours played) - **REGRESSION**

## Unsupervised models

Clustering - grouping observations into similar groups or clusters (e.g. customer or market segmentation)

# Supervised learning types

**Classification** - Target variable is categorical (discrete) (class of outcome) (**classification**)

Will the customer cancel a service subscription?

Is this transaction fraudulent?

What is the profession of this user?

**Regression** - Target variable is continuous (amount of outcome) (**regression**)

Number of product purchases next month

Number of gaming hours next year

Dollars spent on insurance



# Data collection

Machine learning teams should collect all available data to predict desired outcome with the highest degree of accuracy e.g. in case of purchase predictions:

- Customer information

- Purchase history, cancellations, order amount

- Browsing history, logs, errors

- Device details and location

- Product/service usage frequency

- And others...

# Classification example

	Past fraud count	Time of transaction	Declined in T-30 days	Amount
Transaction 1	20	3 am	Yes	5.25 USD
Transaction 2	1	9 pm	Yes	19.5 USD
Transaction 3	0	9.30 am	No	500 USD
Transaction ...				
Transaction N				

Fraud
Yes
Yes
No

# Classification - training

## Use these data points

Transaction 1  
Transaction 2  
Transaction 3  
Transaction ...  
Transaction N

Past fraud count	Time of transaction	Declined in T-30 days	Amount
20	3 am	Yes	5.25 USD
1	9 pm	Yes	19.5 USD
0	9.30 am	No	500 USD

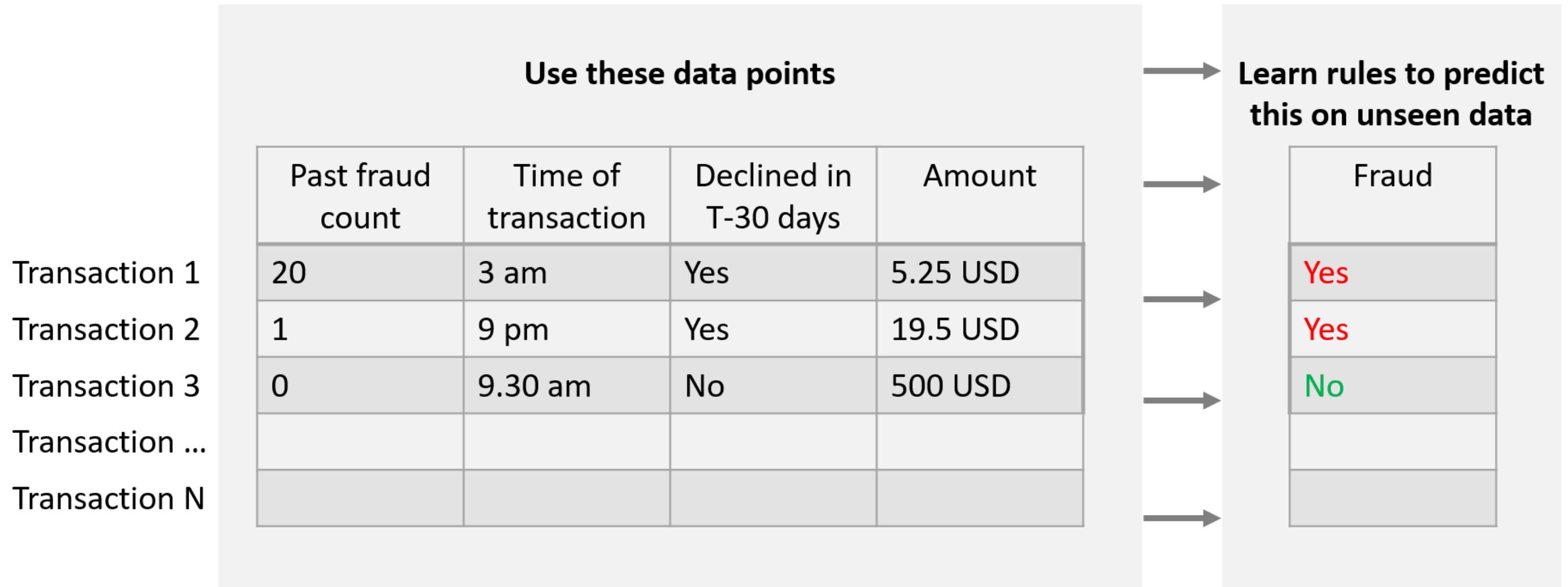
Fraud

Yes

Yes

No

# Classification - learning



# Classification - unseen data

## New unseen data

Transaction 1

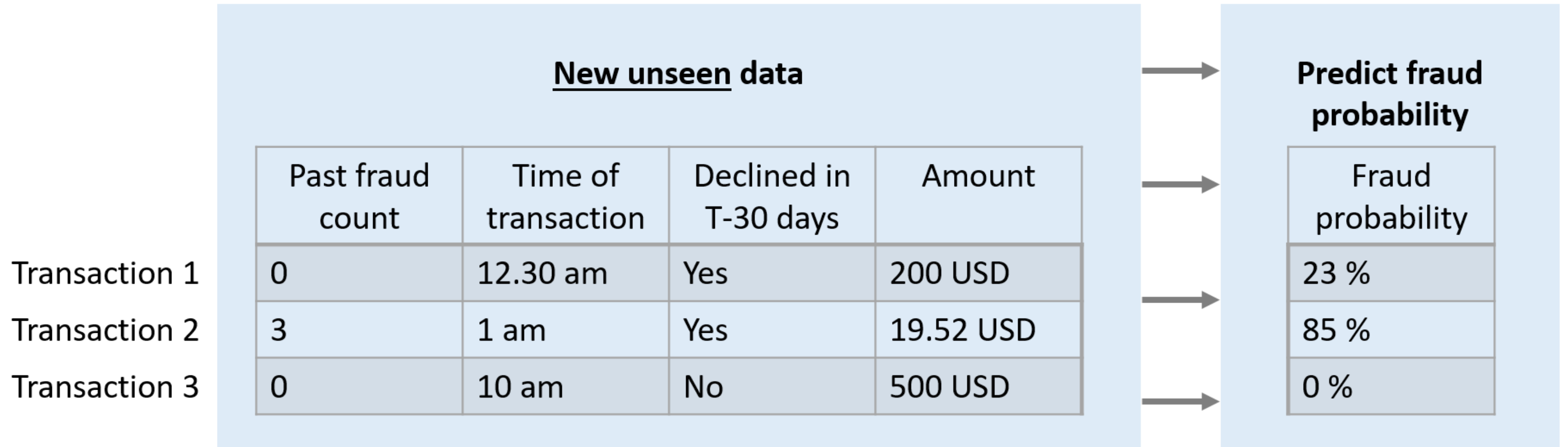
Transaction 2

Transaction 3

Past fraud count	Time of transaction	Declined in T-30 days	Amount
0	12.30 am	Yes	200 USD
3	1 am	Yes	19.52 USD
0	10 am	No	500 USD

Fraud probability

# Classification - prediction



# Regression example

	Last month spend	Recency in days	Average cart value	Store visits per year
Customer 1	845 USD	20	340 USD	32
Customer 2	205 USD	1	100 USD	25
Customer 3	0 USD	55	70 USD	14
Customer ...	...	...	...	...
Customer N	43	114.5	134	61.2

Next month spend
585 USD
150 USD
20 USD
...
69 USD

# Regression - training

## Use these data points

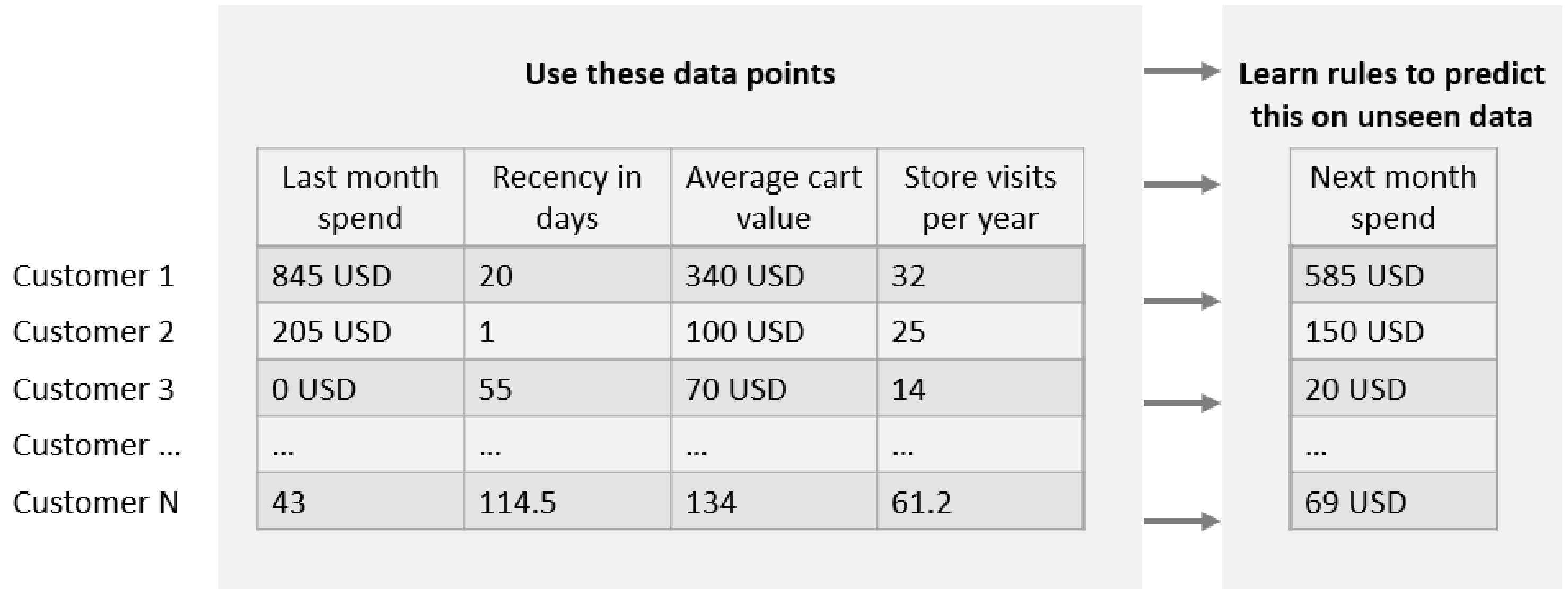
Customer 1  
Customer 2  
Customer 3  
Customer ...  
Customer N

Last month spend	Recency in days	Average cart value	Store visits per year
845 USD	20	340 USD	32
205 USD	1	100 USD	25
0 USD	55	70 USD	14
...	...	...	...
43	114.5	134	61.2

Next month spend
585 USD
150 USD
20 USD
...
69 USD



# Regression - learning

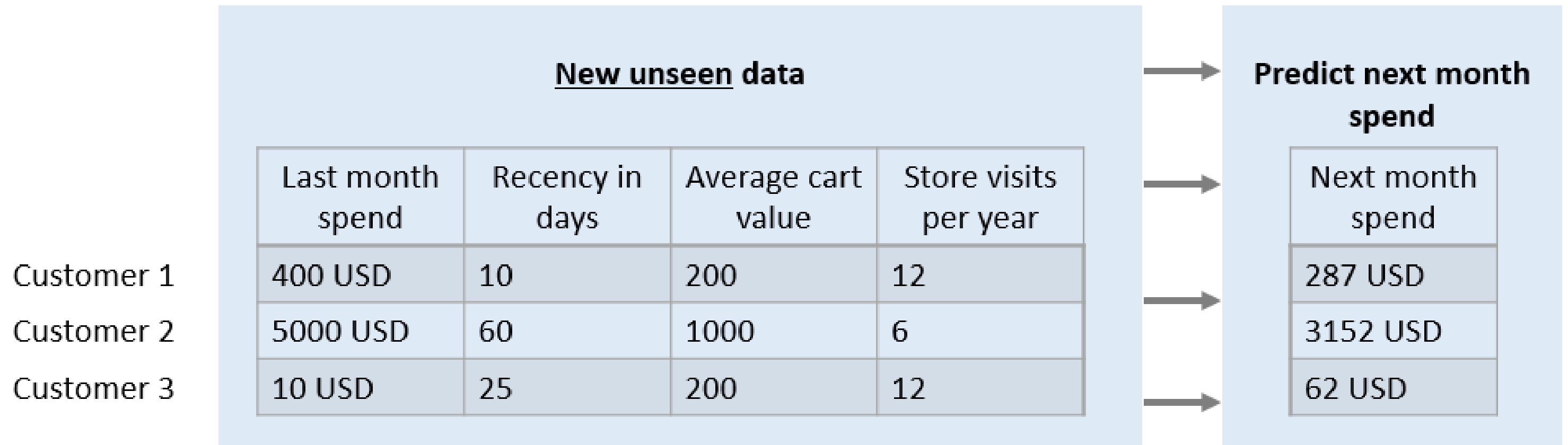


# Regression - unseen data

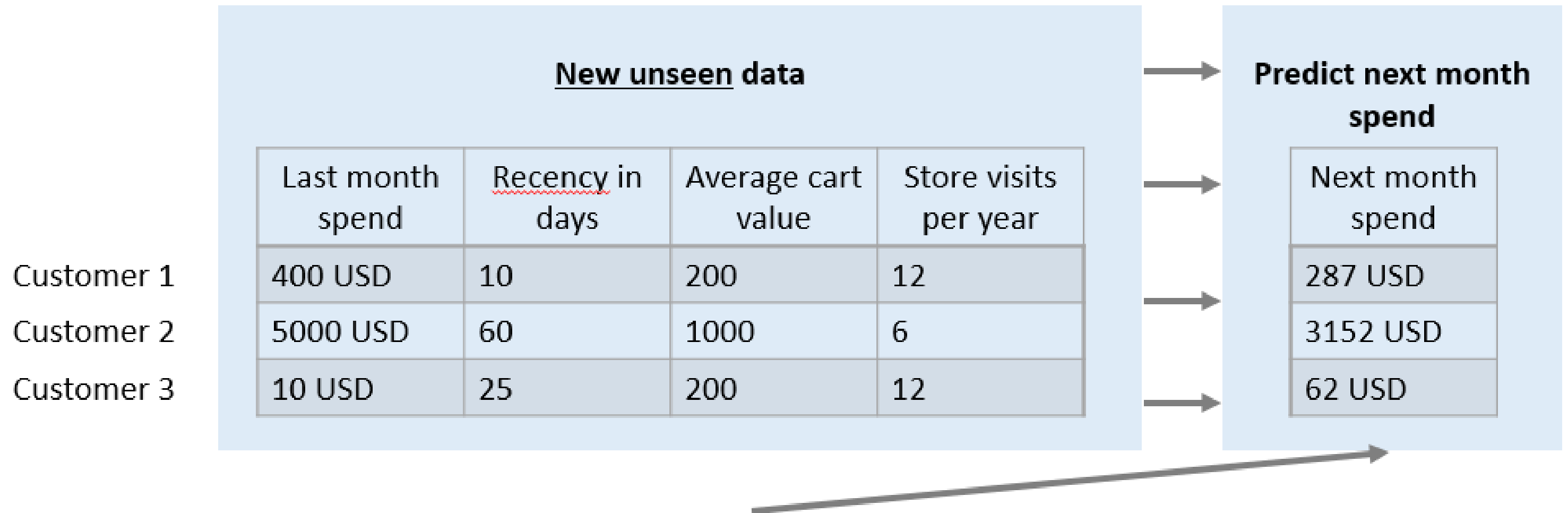
	<u>New unseen data</u>			
	Last month spend	Recency in days	Average cart value	Store visits per year
Customer 1	400 USD	10	200	12
Customer 2	5000 USD	60	1000	6
Customer 3	10 USD	25	200	12

Next month spend

# Regression - prediction



# Regression - actual prediction



These are **real** predictions based from a linear regression model!

# Let's practice!

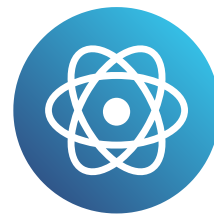
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# Prediction models (unsupervised learning)

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# What is unsupervised machine learning?

## *Unsupervised models*

**Clustering** - grouping observations into similar groups or clusters (e.g. customer or market segmentation)

**Anomaly detection** - detecting which observations fall out of the discovered "regular pattern" and use it as an input in supervised learning or a business input

**Recommender engines** - e.g. recommending products or services to customers based on their similarity to other customers e.g. Netflix movie recommendations

# Clustering example - segmentation

	Annual spend	Recency in days	Store visits per year
Customer 1	8450 USD	20	32
Customer 2	2050 USD	1	25
Customer 3	450 USD	55	14
Customer ...	...	...	...
Customer N	628 USD	114.5	61.2



# Segmentation - data

	Monetary value	Recency	Frequency
Customer 1	8450 USD	20	32
Customer 2	2050 USD	1	25
Customer 3	450 USD	55	14
Customer ...	...	...	...
Customer N	628 USD	114.5	61.2

# Segmentation - training

Use these data points

Customer 1  
Customer 2  
Customer 3  
Customer ...  
Customer N

Monetary value	Recency	Frequency
8450 USD	20	32
2050 USD	1	25
450 USD	55	14
...	...	...
628 USD	114.5	61.2

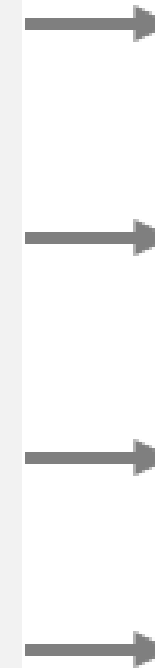
# Segmentation - discover

Customer 1  
Customer 2  
Customer 3  
Customer ...  
Customer N

Use these data points

Monetary value	Recency	Frequency
8450 USD	20	32
2050 USD	1	25
450 USD	55	14
...	...	...
628 USD	114.5	61.2

To identify similar segments of customers

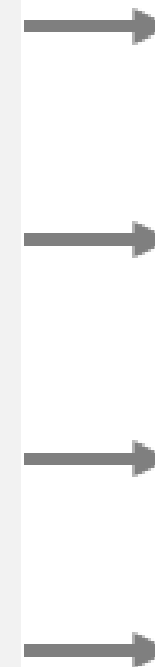


# Segmentation - analyze

Customer 1  
Customer 2  
Customer 3  
Customer ...  
Customer N

Use these data points

Monetary value	Recency	Frequency
8450 USD	20	32
2050 USD	1	25
450 USD	55	14
...	...	...
628 USD	114.5	61.2



To identify similar segments of customers

1  
2  
3

Monetary value	Recency	Frequency
4788	76	74
8872	21	34
1312	29	21

# Let's practice!

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