

Case Study: Optimizing Product Prices Using Machine Learning



Janani Ravi

Co-founder, Loonycorn

www.loonycorn.com

Overview

Price elasticity of demand

**Case Study: Price Optimization in
Fashion E-commerce**

Price Elasticity of Demand

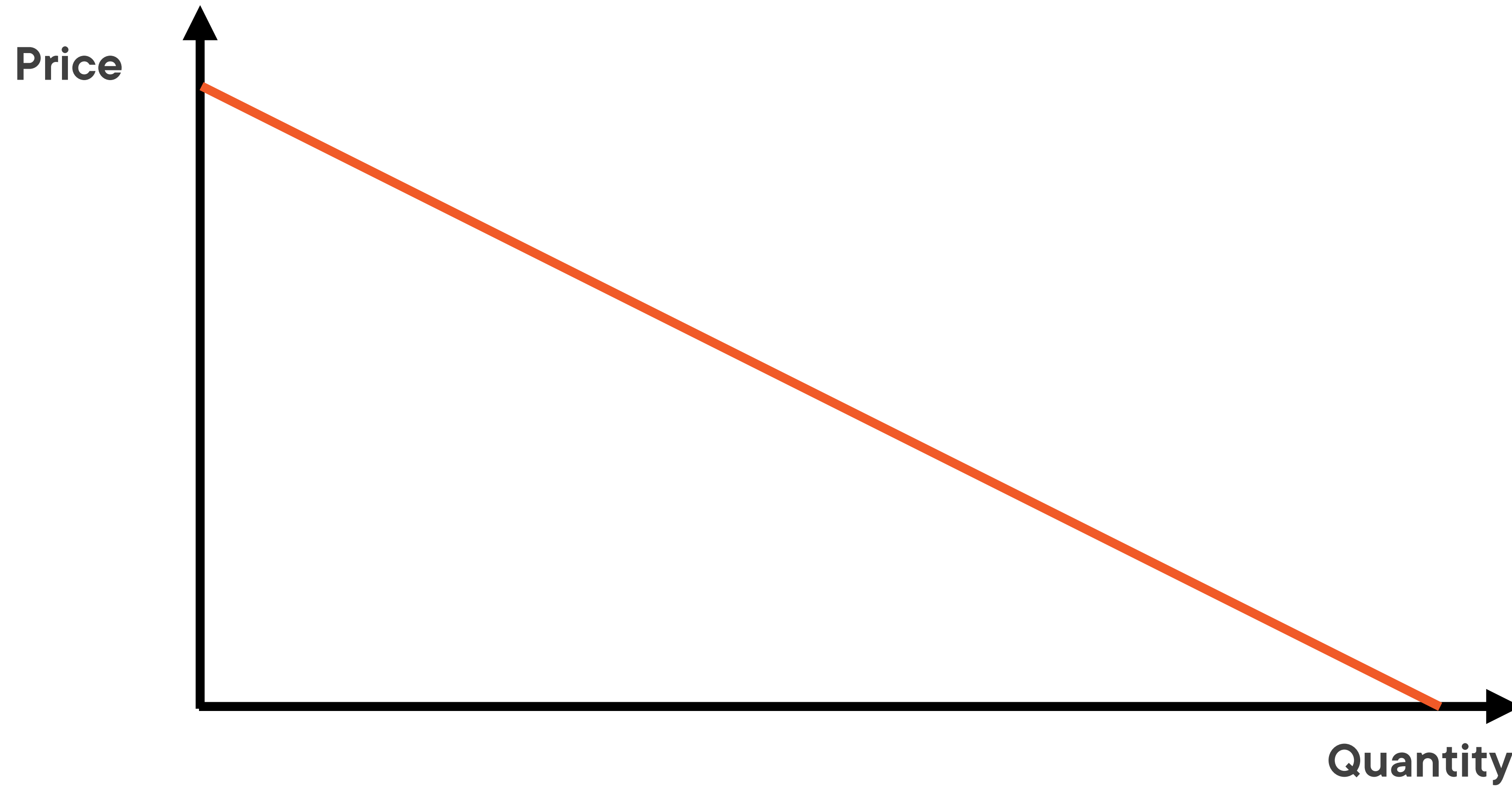
Law of Demand

If all other factors remain equal, the higher the price of a good, fewer people will demand that good.

Demand Curve



Demand Curve



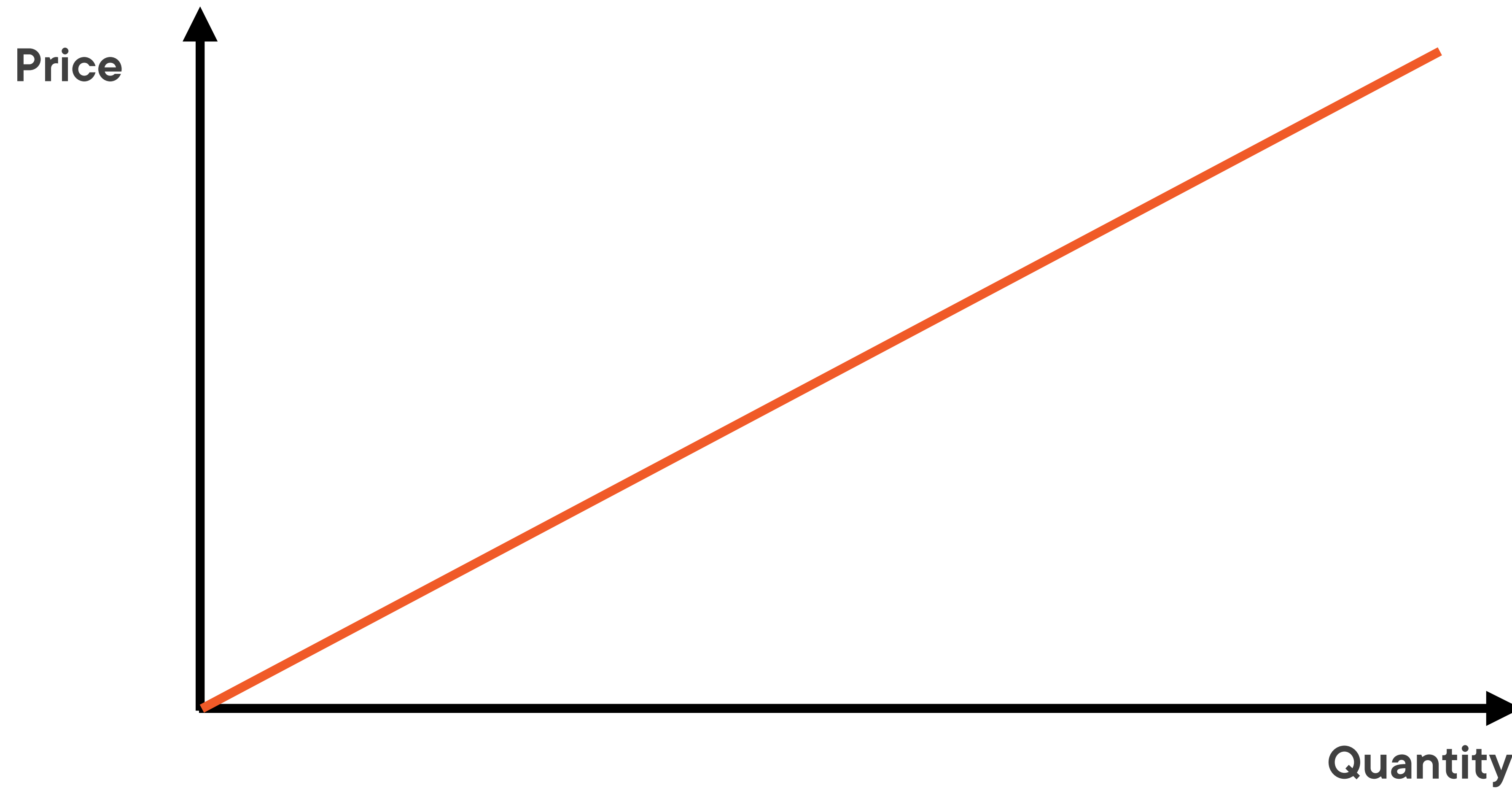
Law of Supply

If all other factors remain equal, the higher the price of a good, higher the quantity supplied

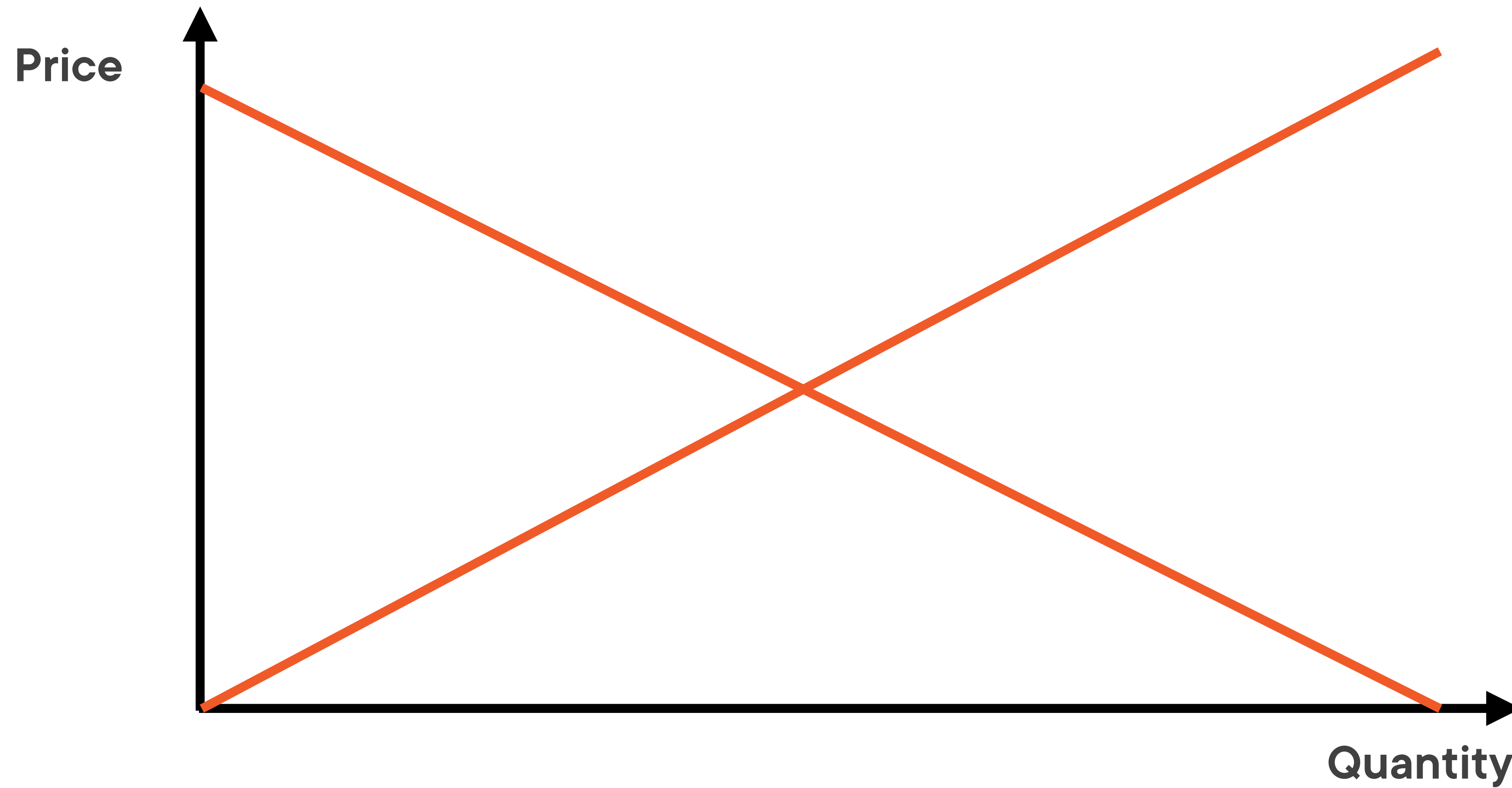
Supply Curve



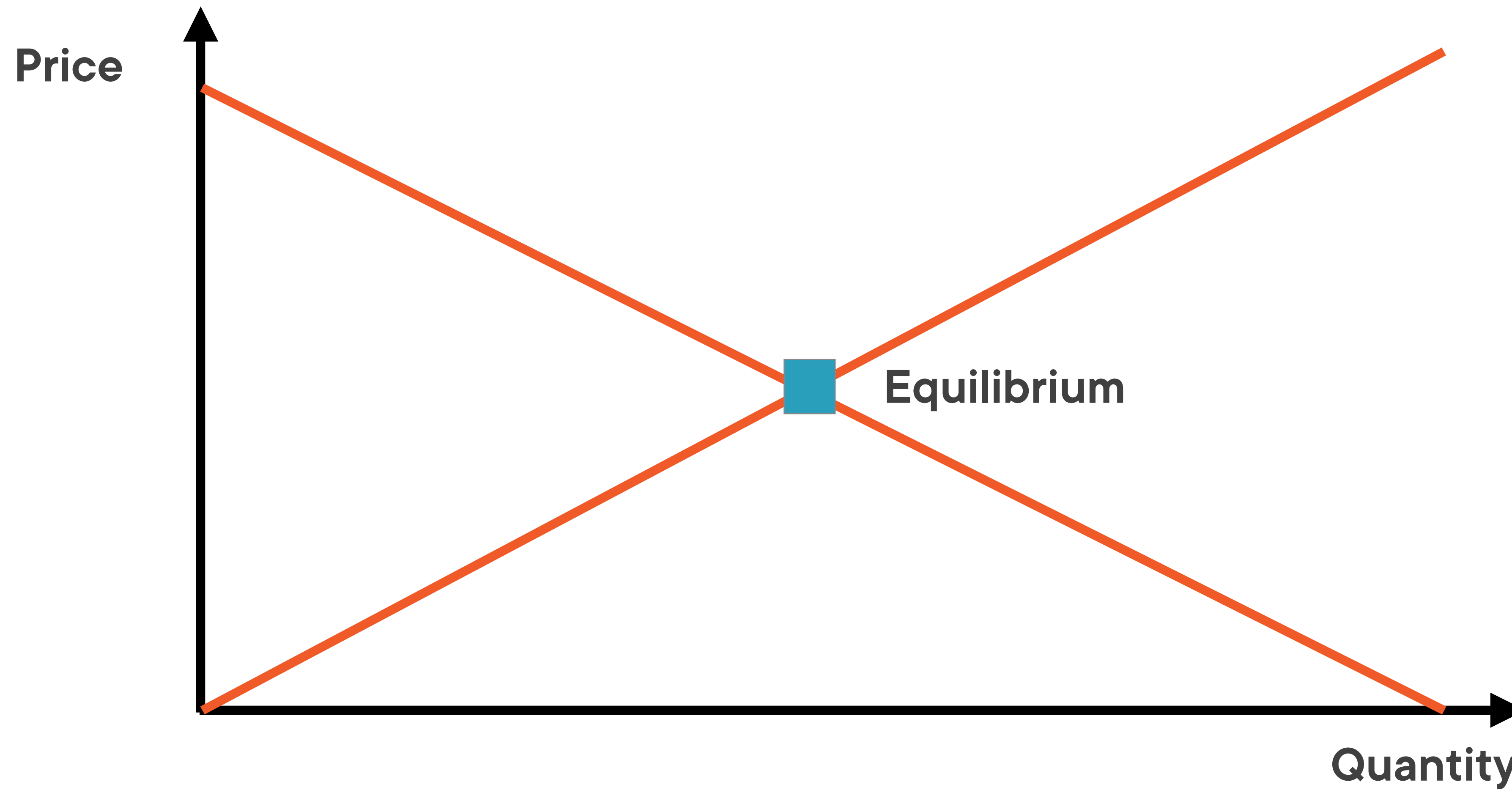
Supply Curve



Law of Supply and Demand



Law of Supply and Demand



Elasticity of Demand

Refers to how sensitive demand for a good is compared to changes in other economic factors such as price or income

Elasticity of Demand

Refers to how **sensitive** demand for a good is compared to changes in other economic factors such as price or income

Elasticity of Demand

**Price elasticity of
demand**

**Income elasticity
of demand**

**Substitute
elasticity of
demand**

Elasticity of Demand

Price elasticity of demand

Income elasticity of demand

Substitute elasticity of demand

Price Elasticity of Demand

Price elasticity of demand is a measure of the change in the quantity purchased of a product in relation to a change in its price.

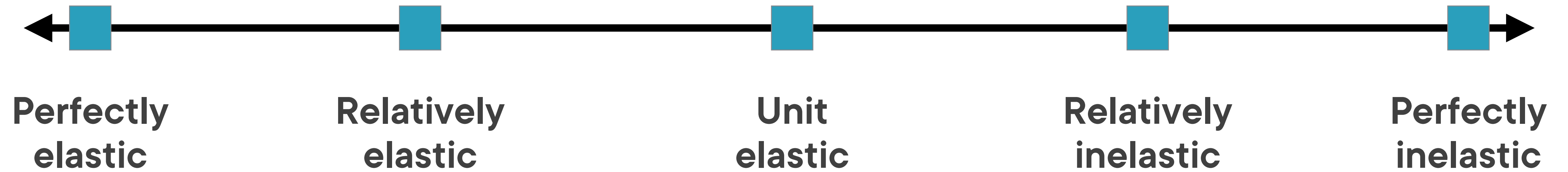
Price Elasticity of Demand

$$\text{Price elasticity of demand} = \frac{\text{Percentage change in quantity demanded}}{\text{Percentage change in price}}$$

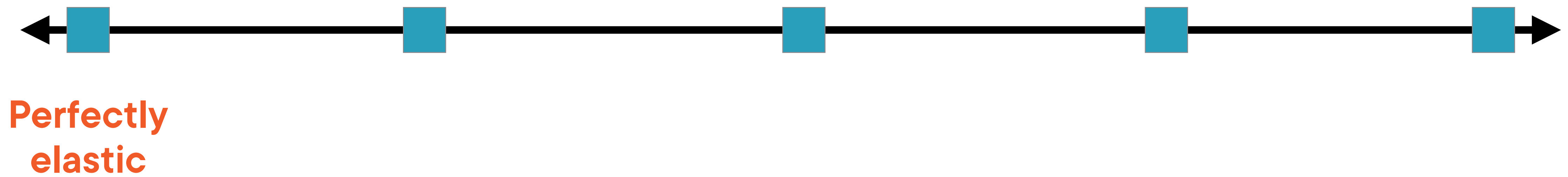
Price Elasticity of Demand



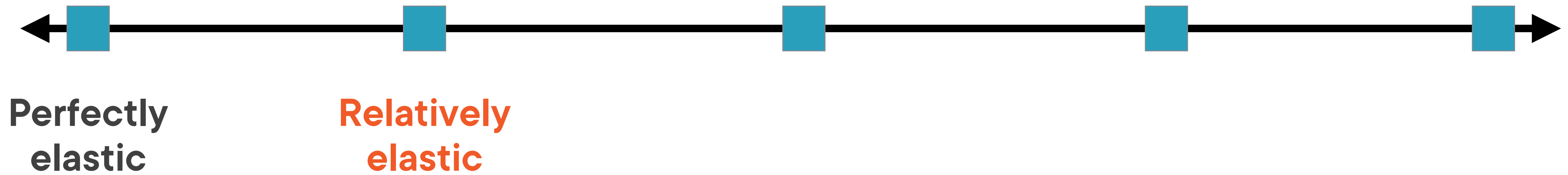
Price Elasticity of Demand



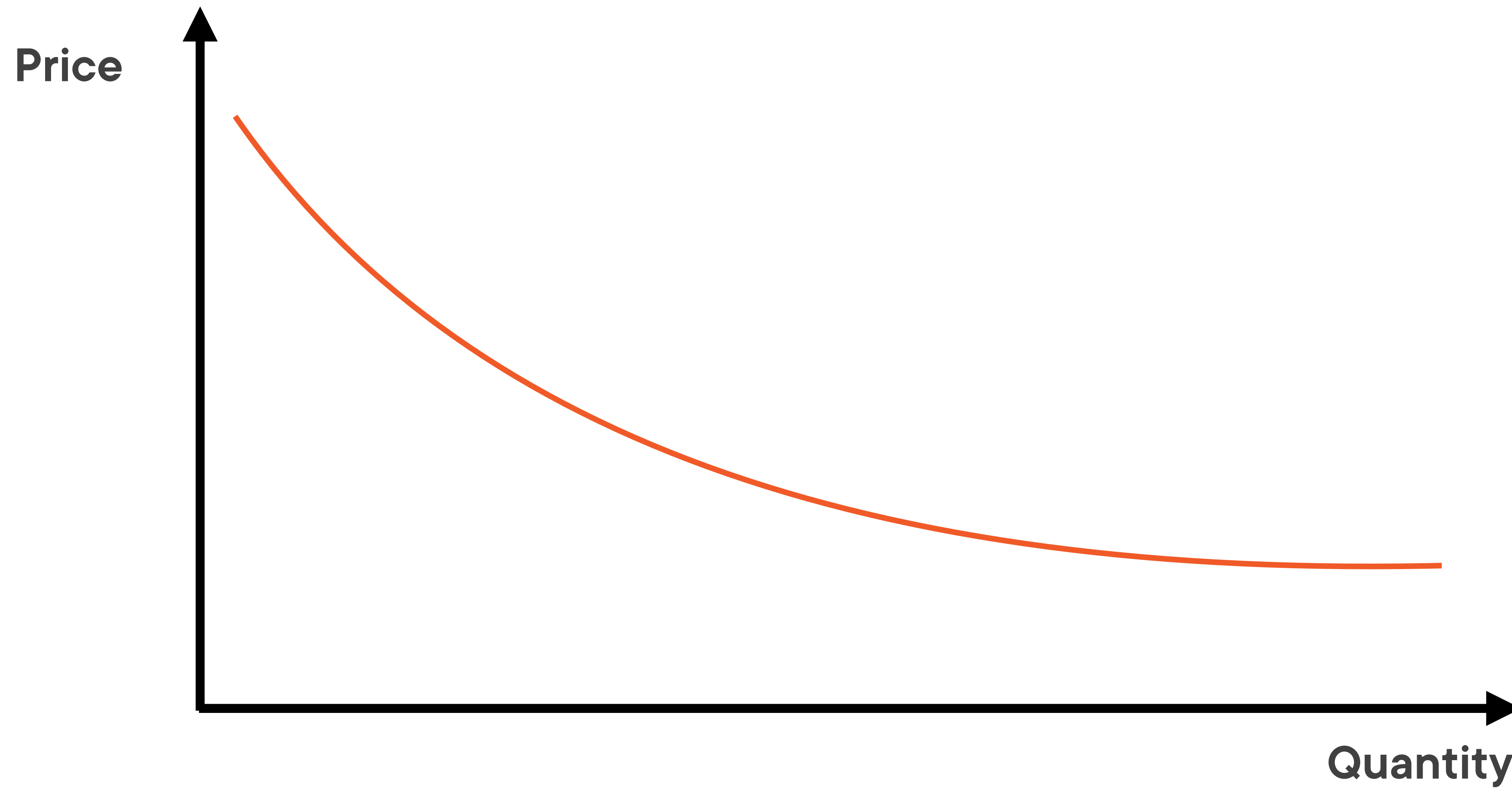
Price Elasticity of Demand



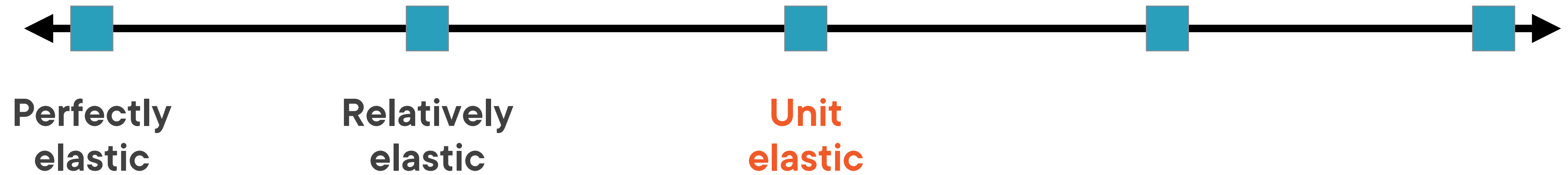
Price Elasticity of Demand



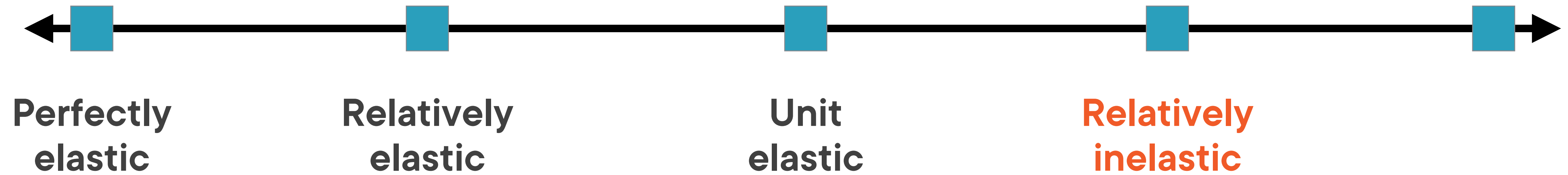
Elastic Demand: Mobile Phones



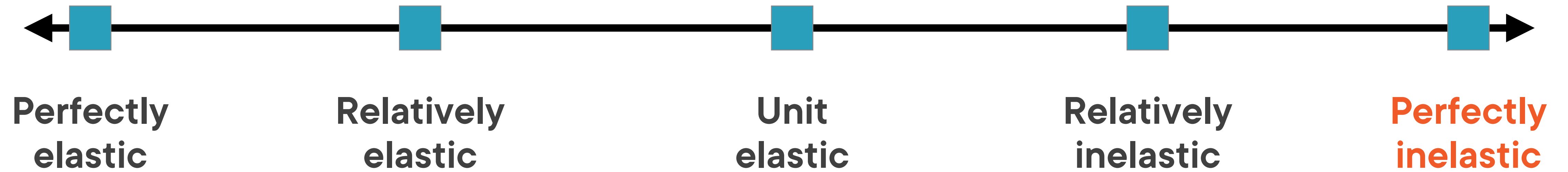
Price Elasticity of Demand



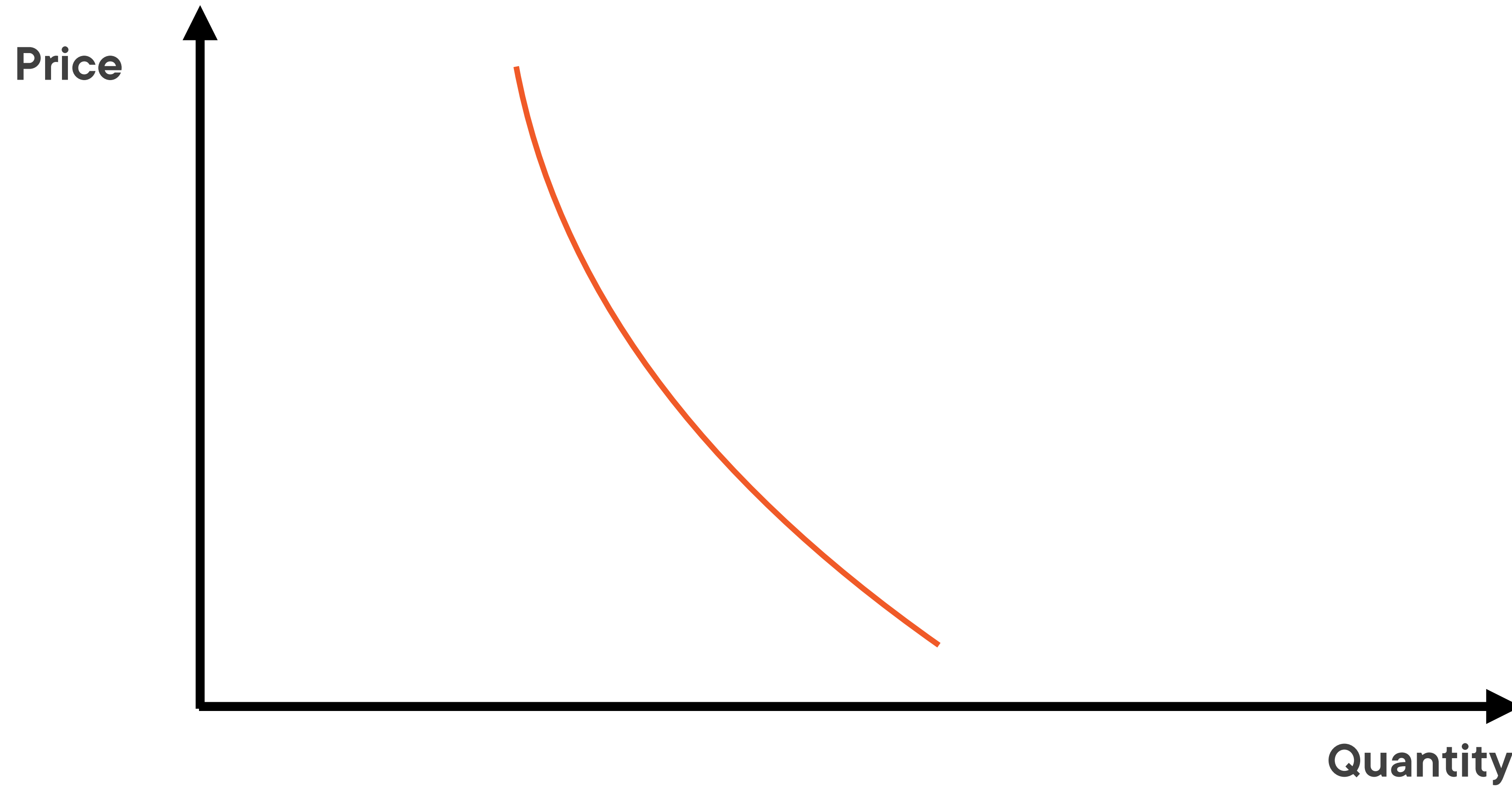
Price Elasticity of Demand



Price Elasticity of Demand



Inelastic Demand: Bread



Any firm's goal would be to move
their products **from relatively
elastic to relatively inelastic**

Optimal Price Point

The price point of a product at which the total profit of the seller is maximized

Case Study: Price Optimization in Fashion E-commerce



Background and Context

Background and context of research paper and,
overview of steps and challenges faced

Fashion E-commerce: Optimal Price Point



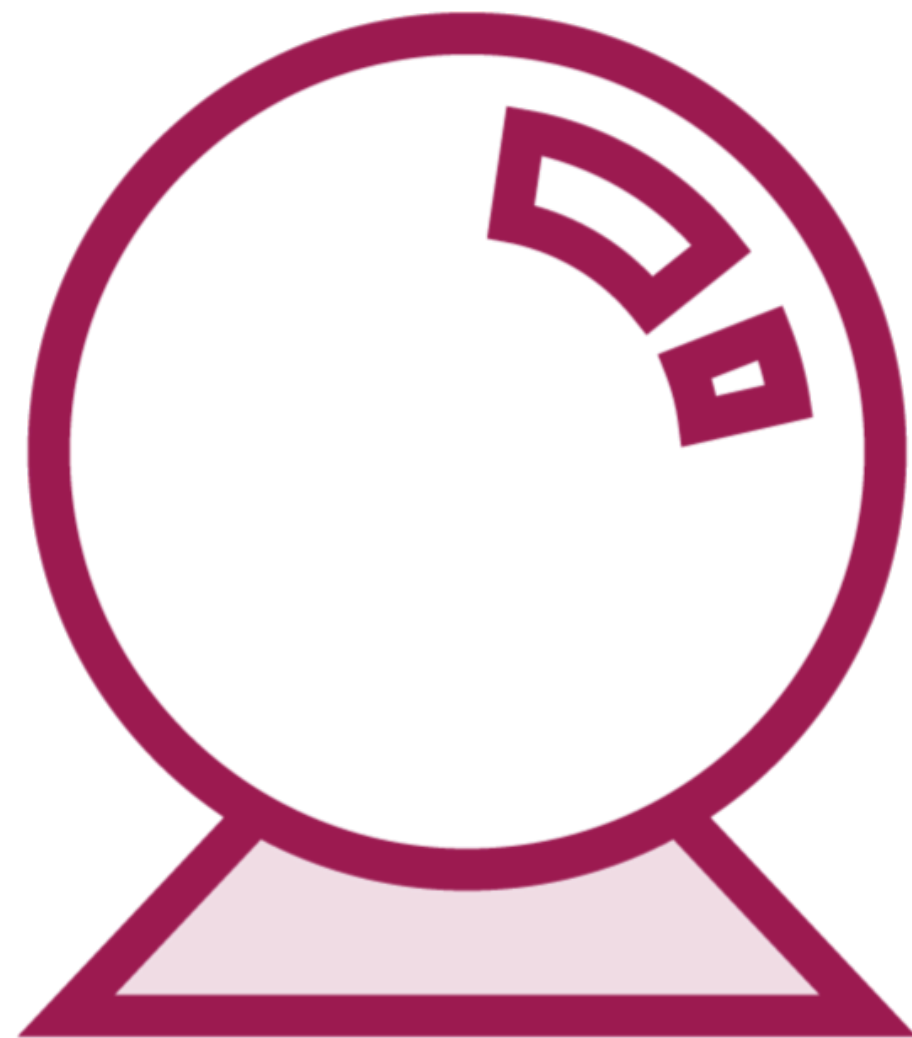
Optimal price point maximizes revenue and profit for the company

Use machine learning and optimization techniques to find optimal price points across products in many categories

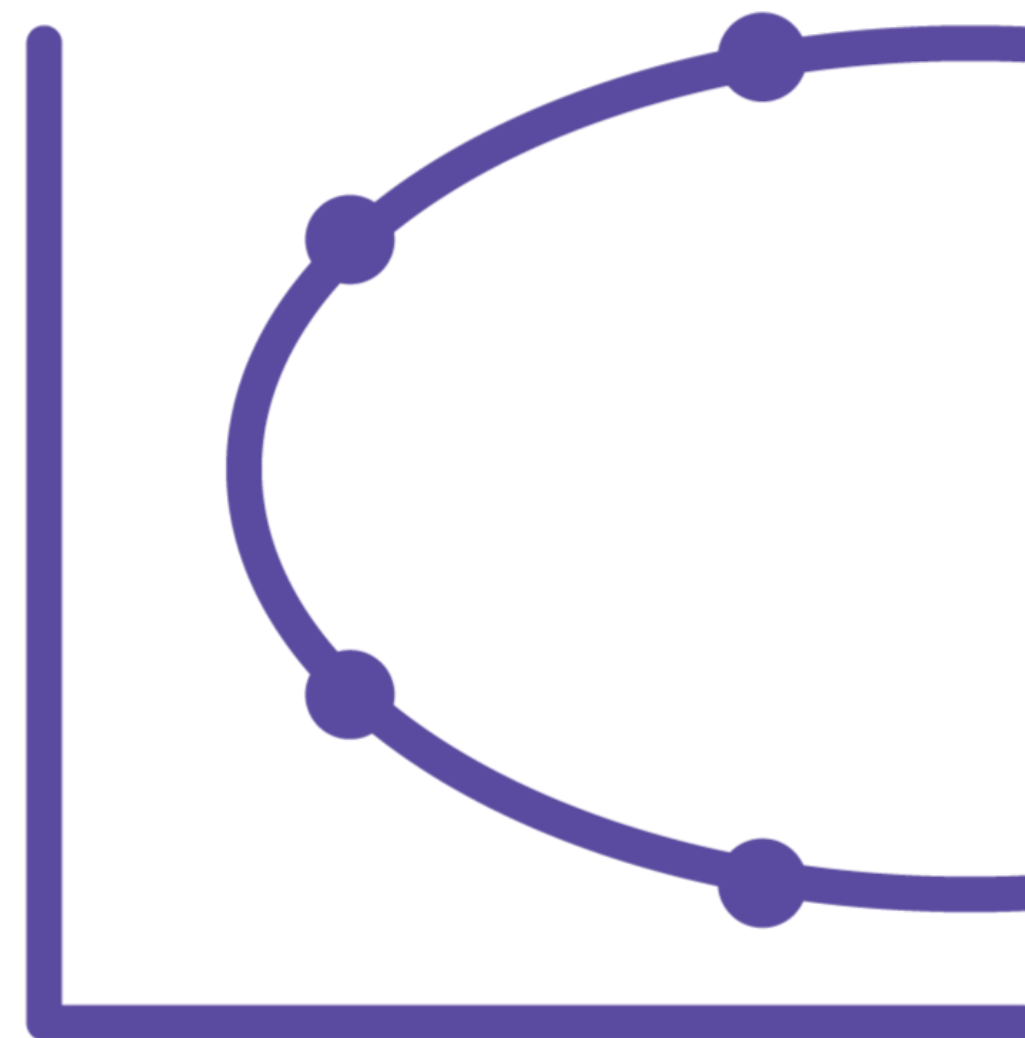
Myntra: Leading Indian fashion e-commerce company

<https://arxiv.org/pdf/2007.05216v2.pdf>

Three Main Components



**Demand prediction
model**

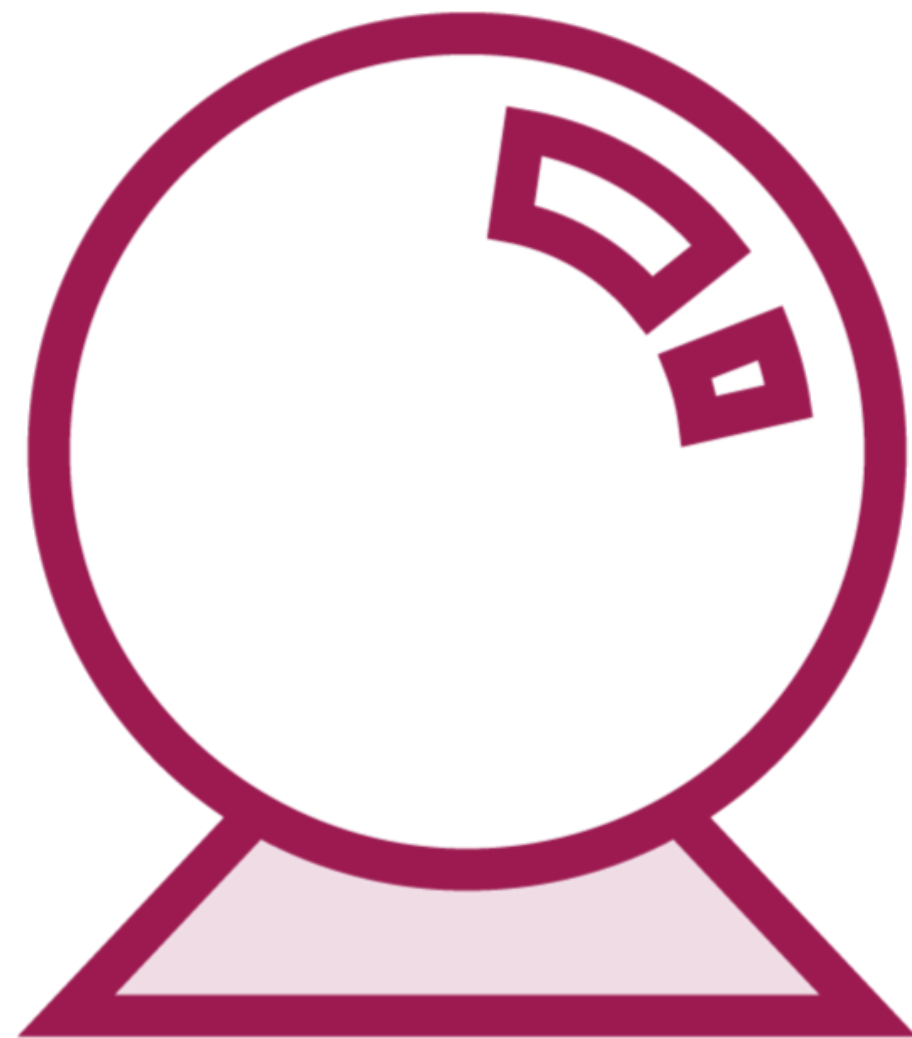


**Compute price elasticity
of demand**

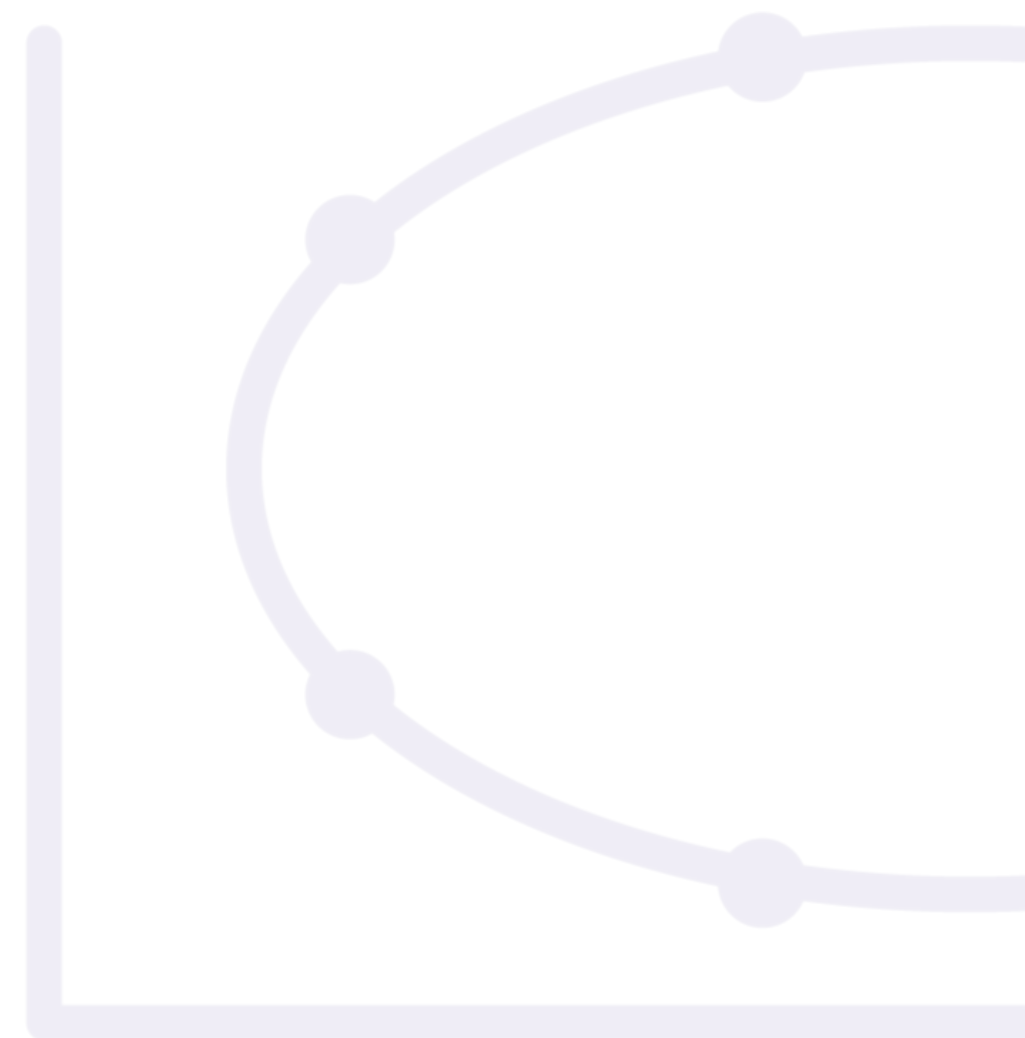


**Linear programming
optimization**

Three Main Components



**Demand prediction
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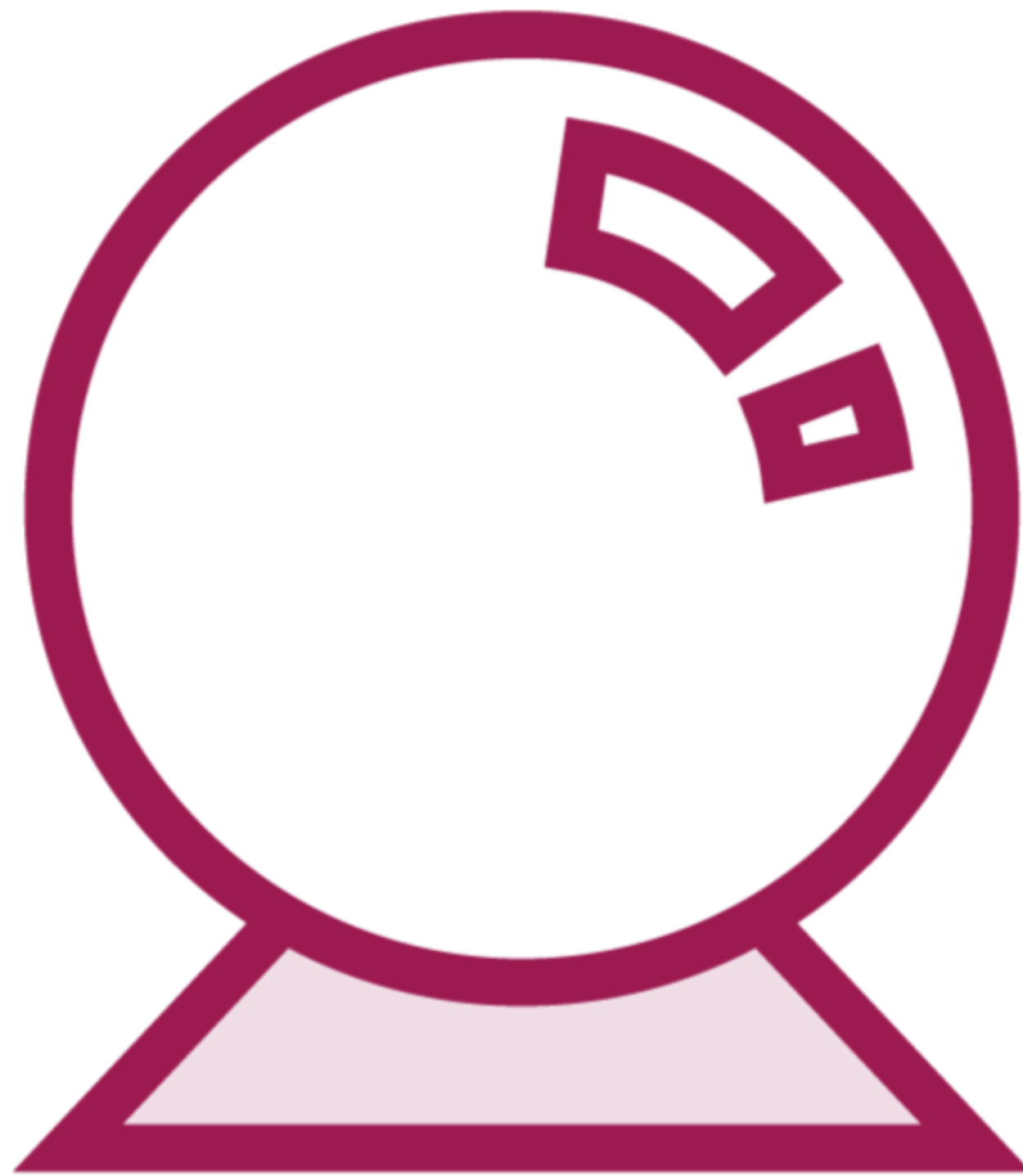


Compute price elasticity
of demand



Linear programming
optimization

Demand Prediction Model

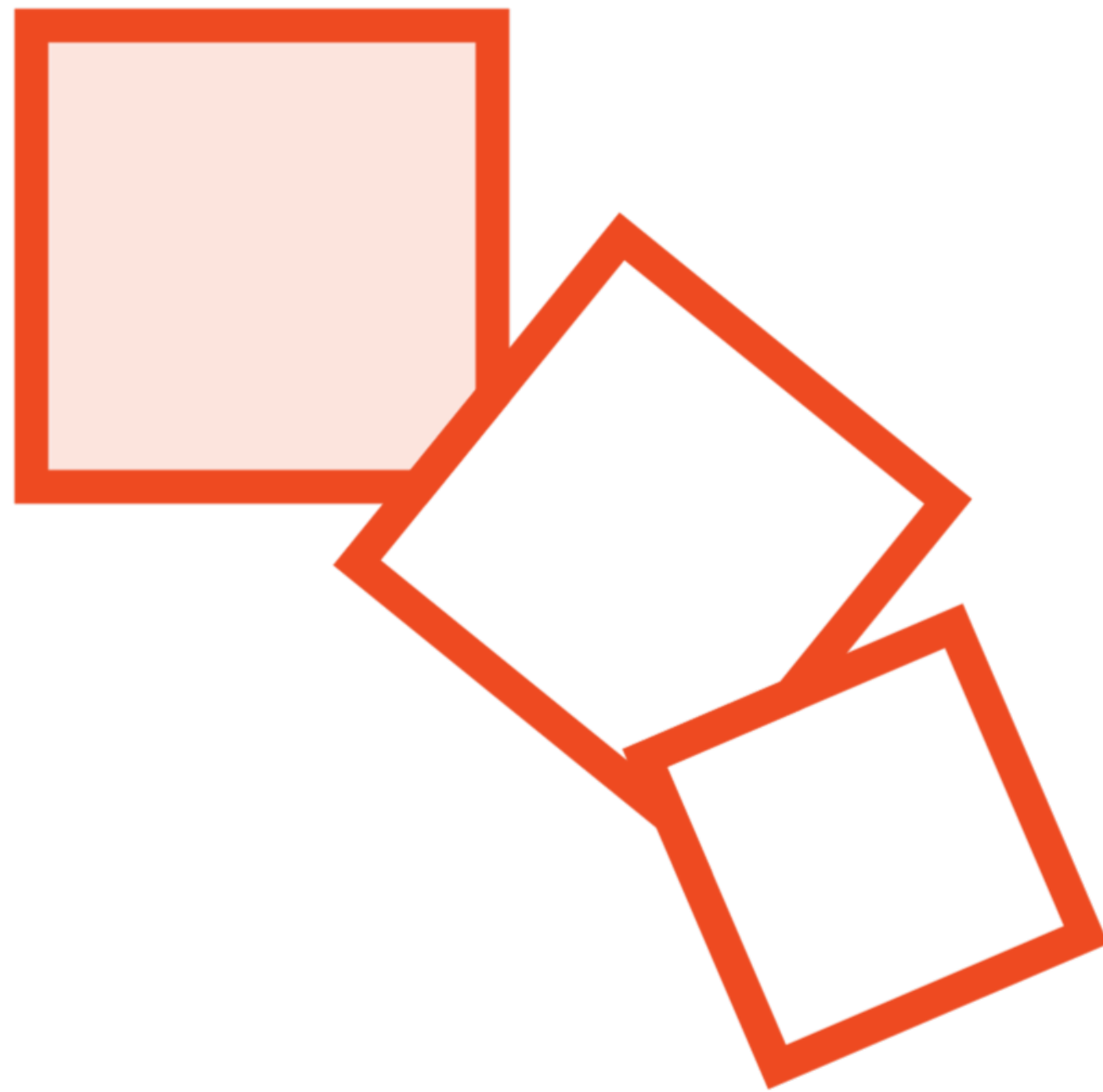


Predict the next day's demand for each product at a certain discount

Discounted prices have better click-through and conversion rates

Model trained on historical sales and browsing clickstream data

Cannibalization Across Brands



Can lead to cannibalization among products on the platform

Increasing the discount on a product might reduce sales of a competing product

To overcome this:

Model run at a category level

Created features at a brand level

Cold-start Problem



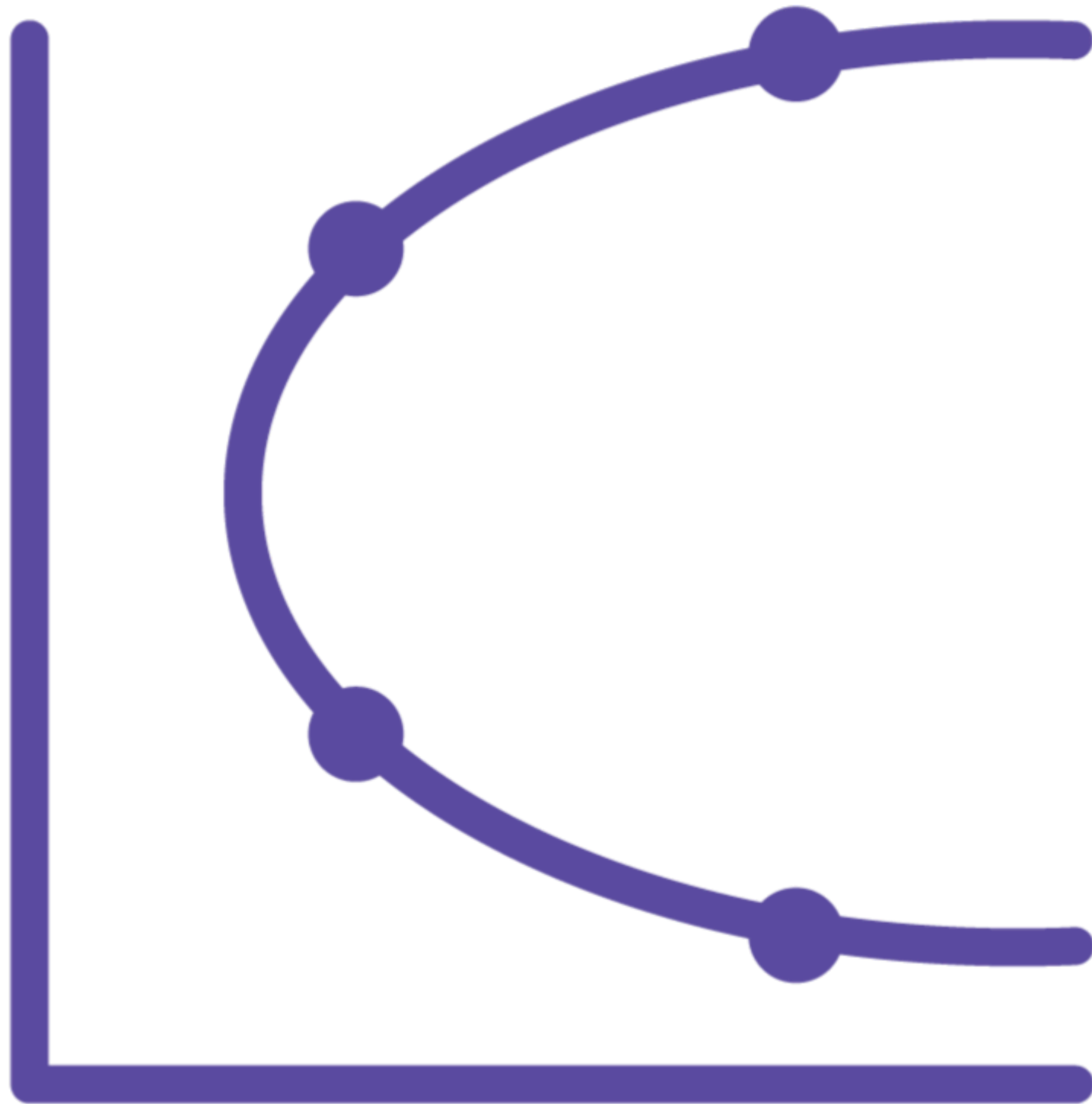
Predicting demand for new products with no browsing or sales history

Used deep-learning models to learn product embeddings

Embeddings used as features in the demand prediction model

Generates demand for all
products for the next day at the
base discount value

Price Elasticity of Demand



Use price elasticity of demand to get demand at different discount values

Gives multiple price-demand pairs for each product

Select a single price point for every product to maximize revenue

Linear Programming



Use linear programming to find the right optimal price for every product

Objective function to maximize revenue

Deployed solution and ran A/B tests
on regular vs. optimized prices



Methodology and Results

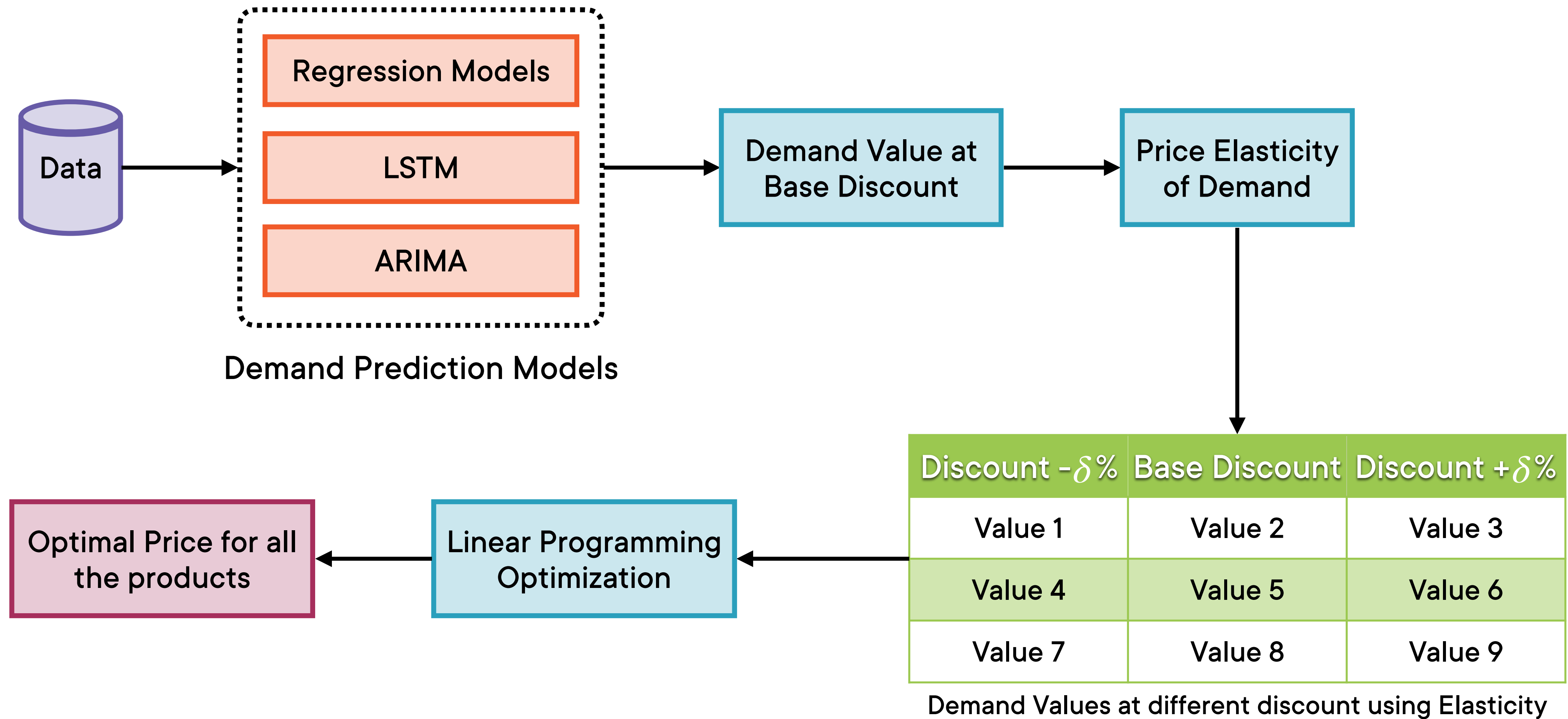
Data sources, feature engineering,
models used, and results

Optimal Price Points for all Products

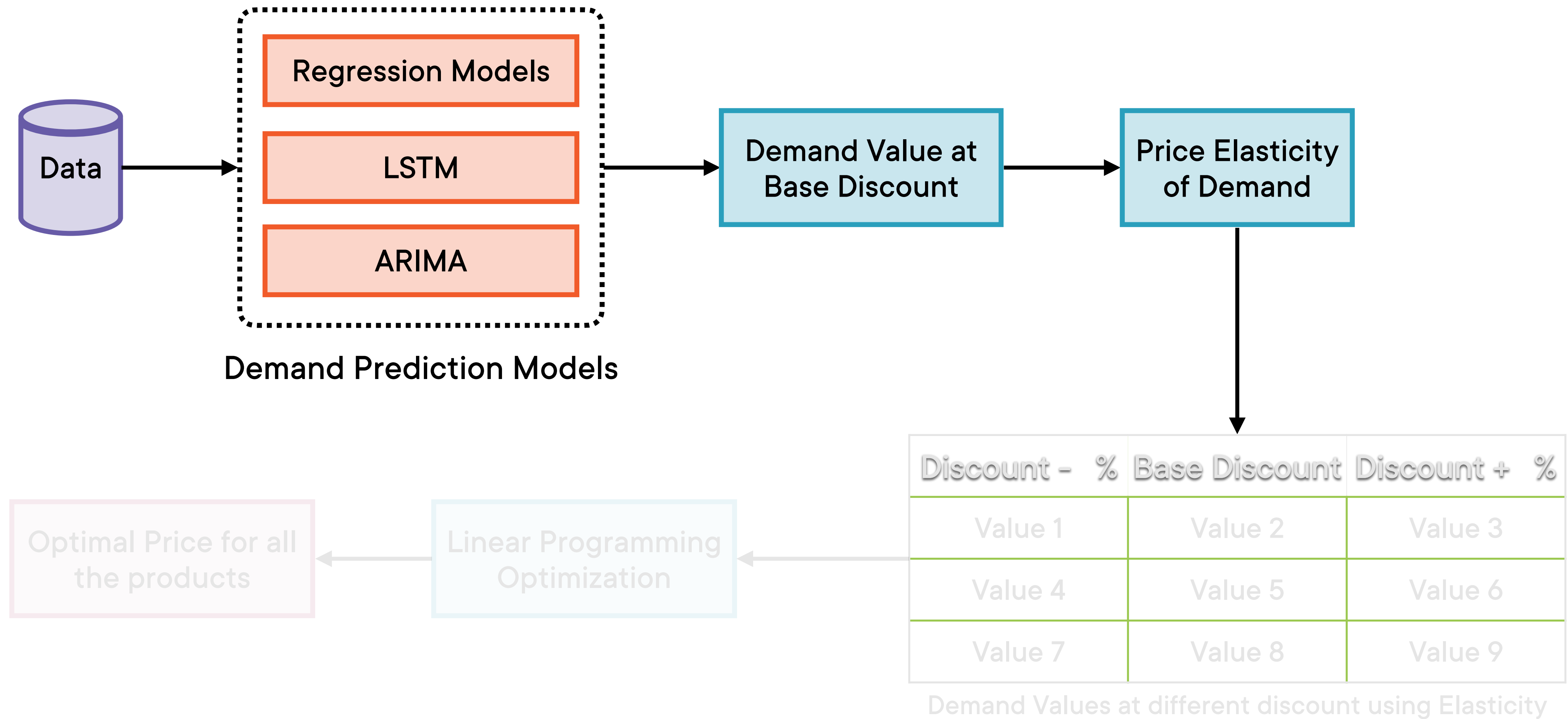
$$R = \sum_{i=1}^n p_i, q_i$$

p_i is the price assigned to the i^{th} product
and q_i is the quantity sold of the i^{th} product

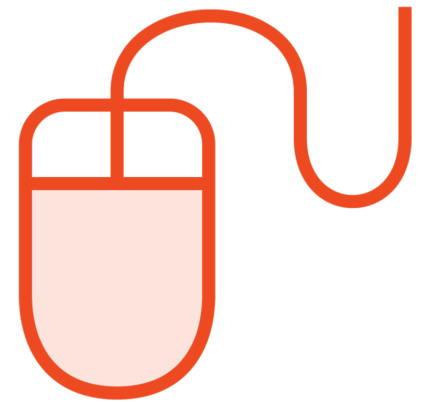
Price Optimization Workflow



Price Optimization Workflow



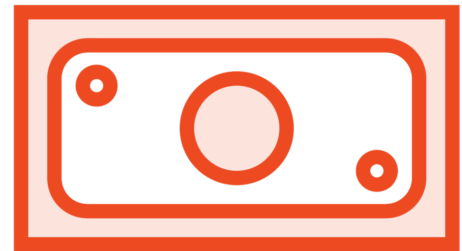
Data Sources



Clickstream data: User activity such as clicks, carts, orders etc.



Product catalog: Details of a product like brand, color, price, and other attributes

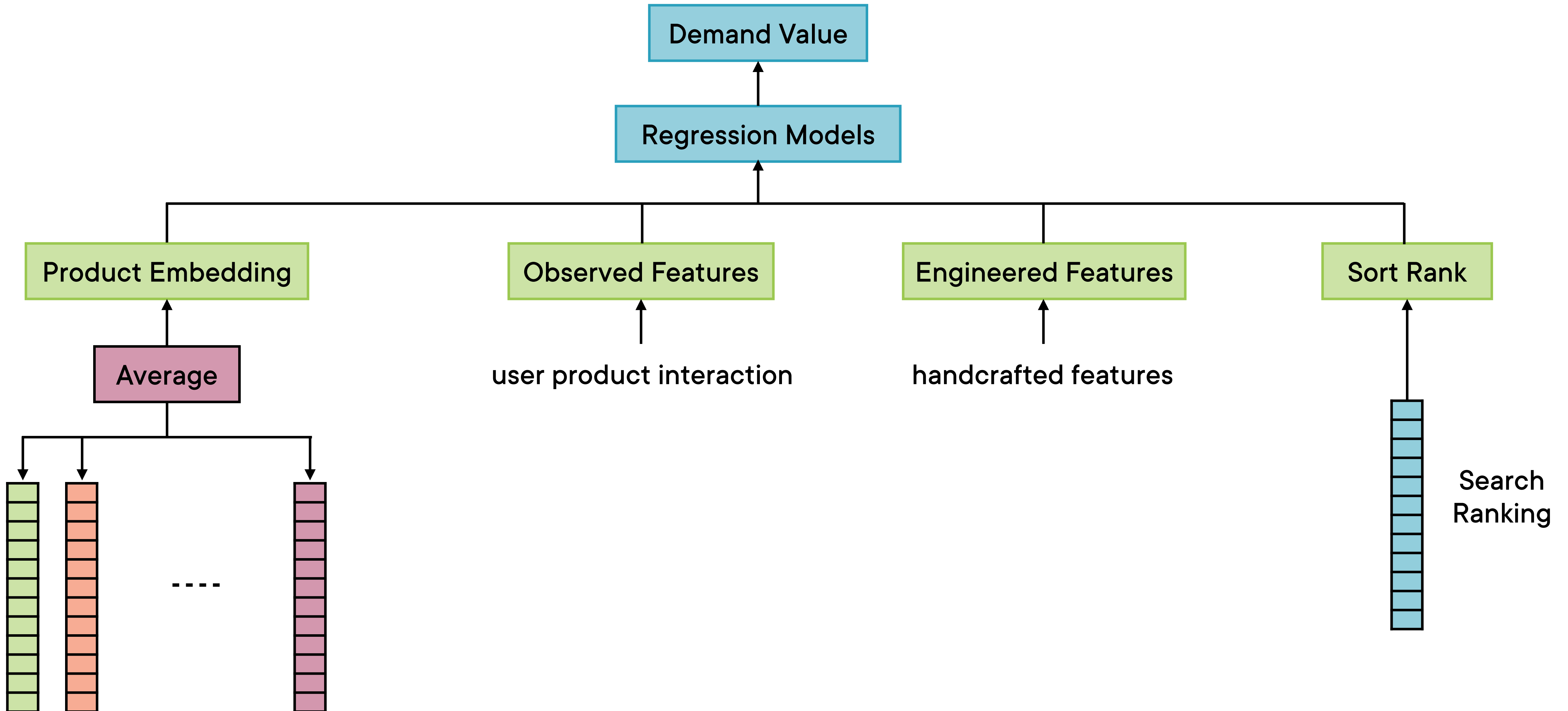


Price data: Price and quantity of product sold at hour-level granularity

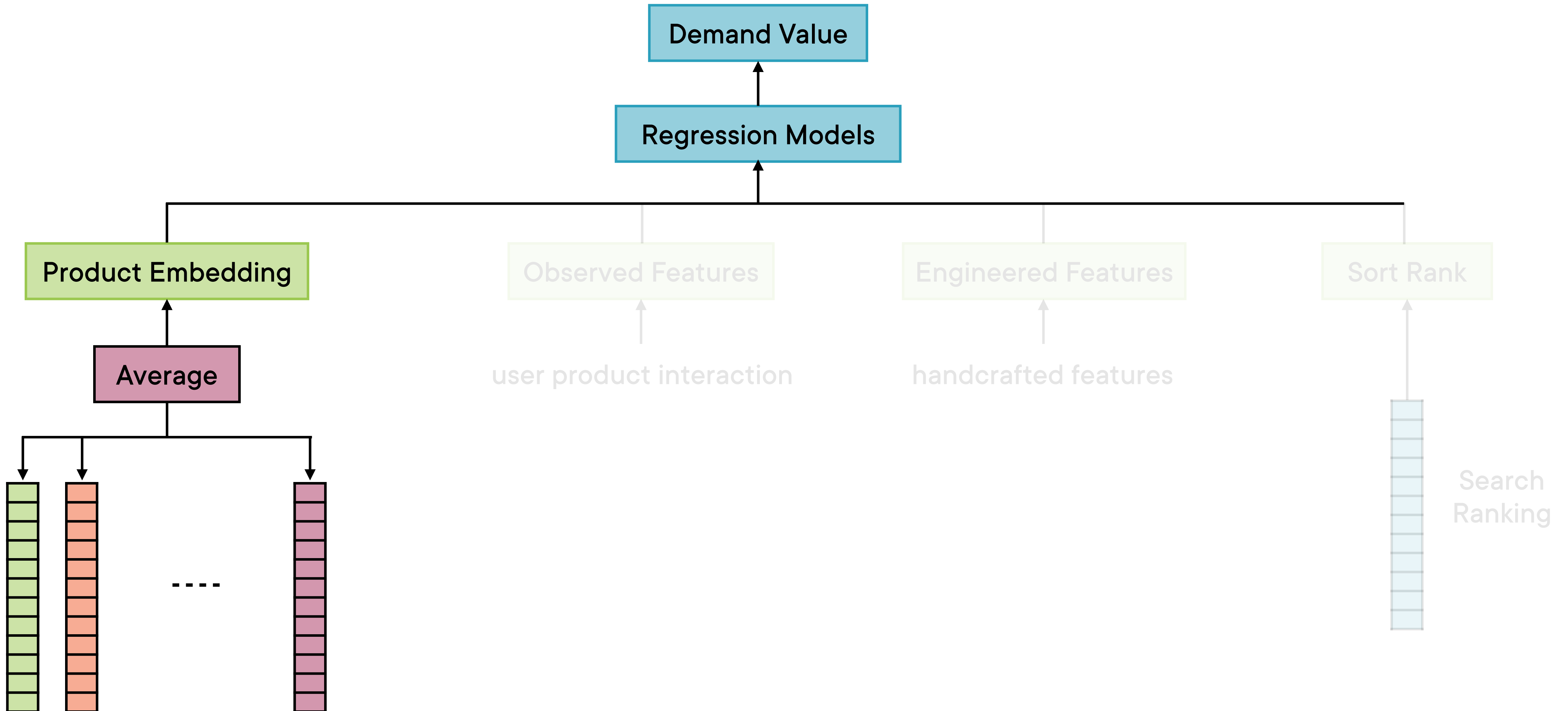


Sort rank: Search rank and corresponding scores for all live products on the platform

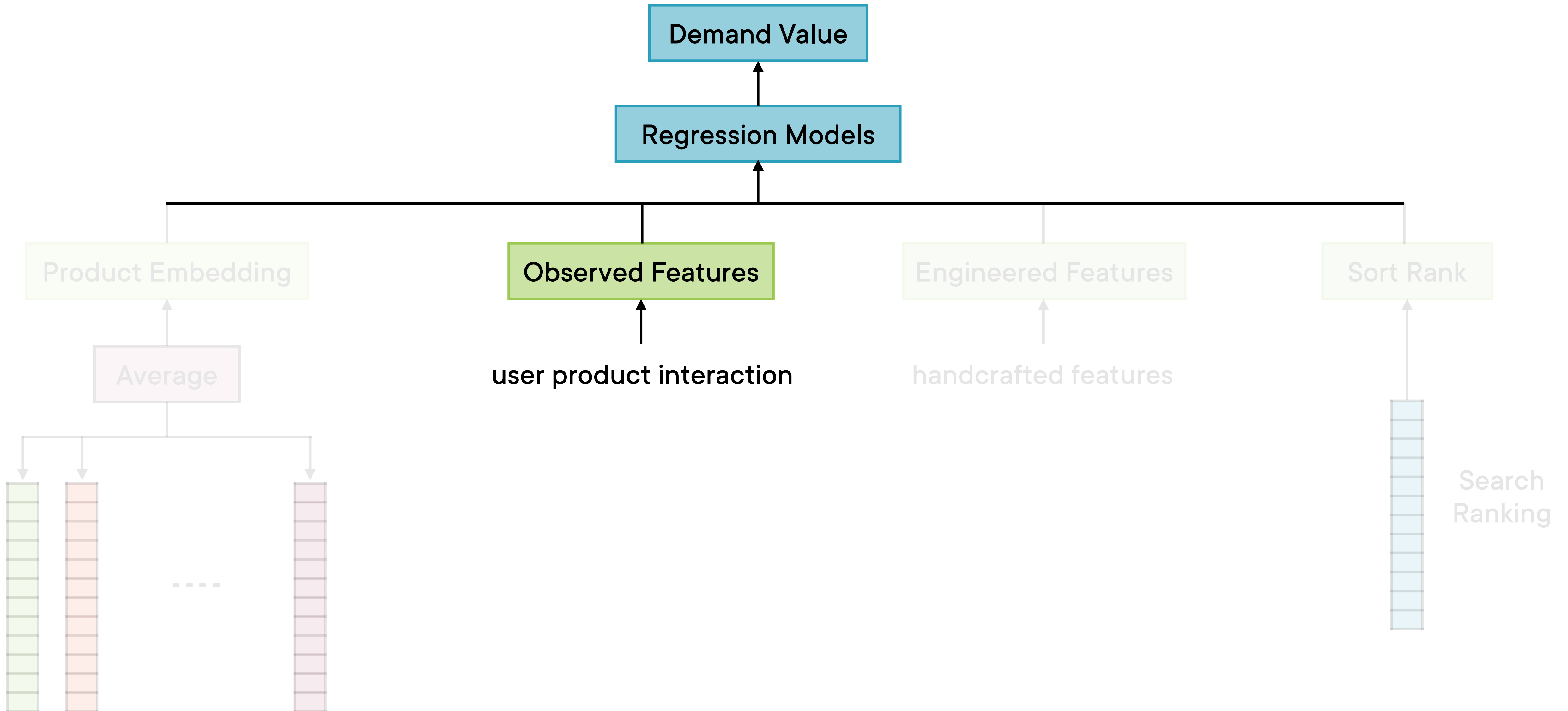
Feature Engineering



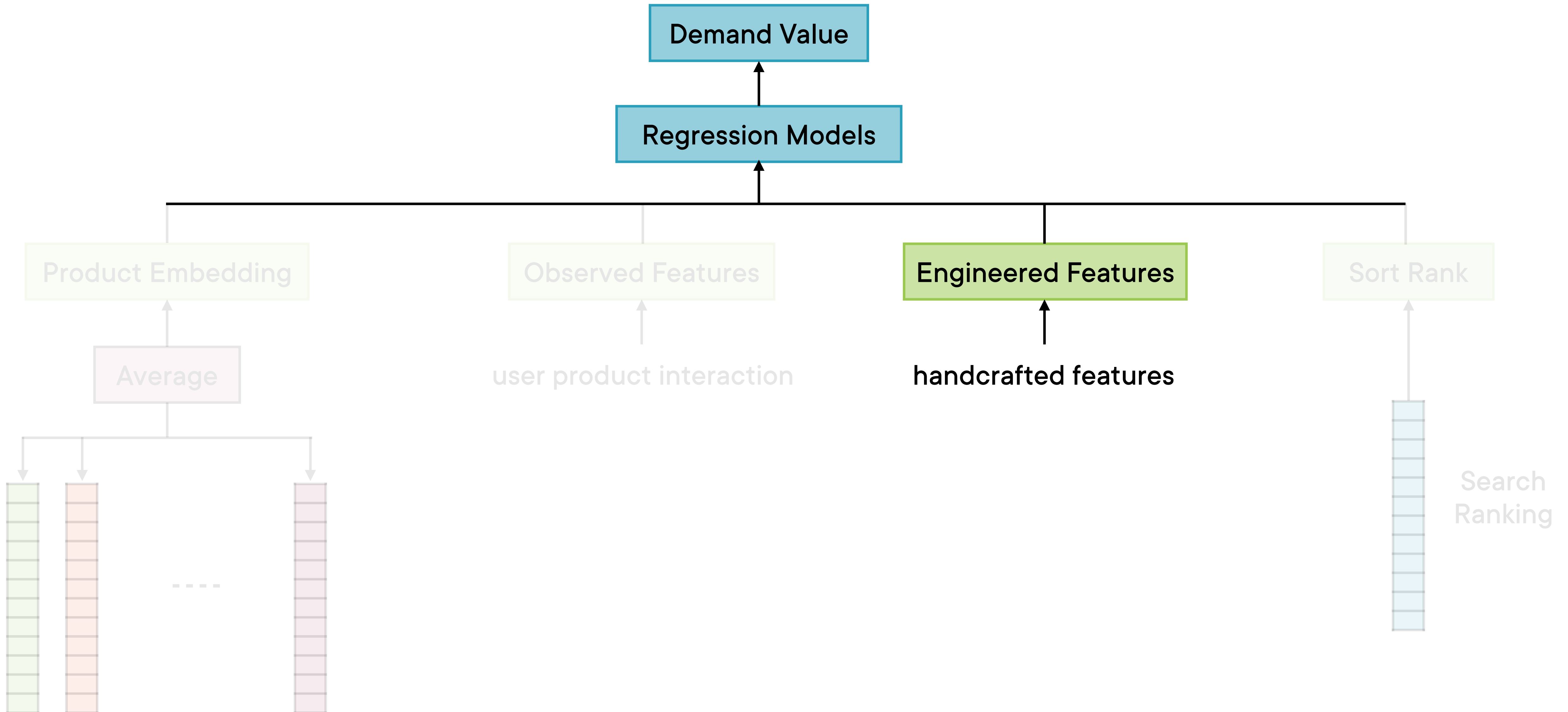
Feature Engineering



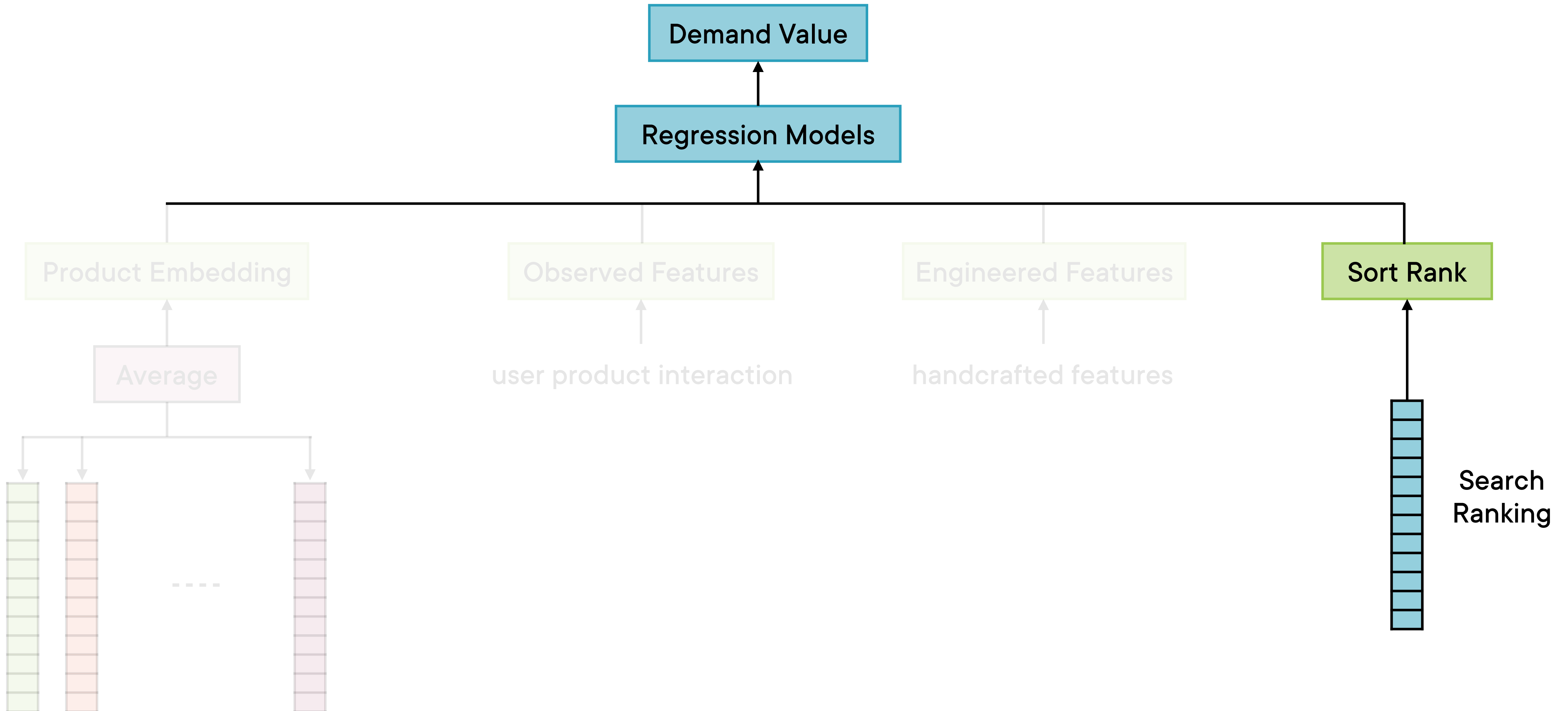
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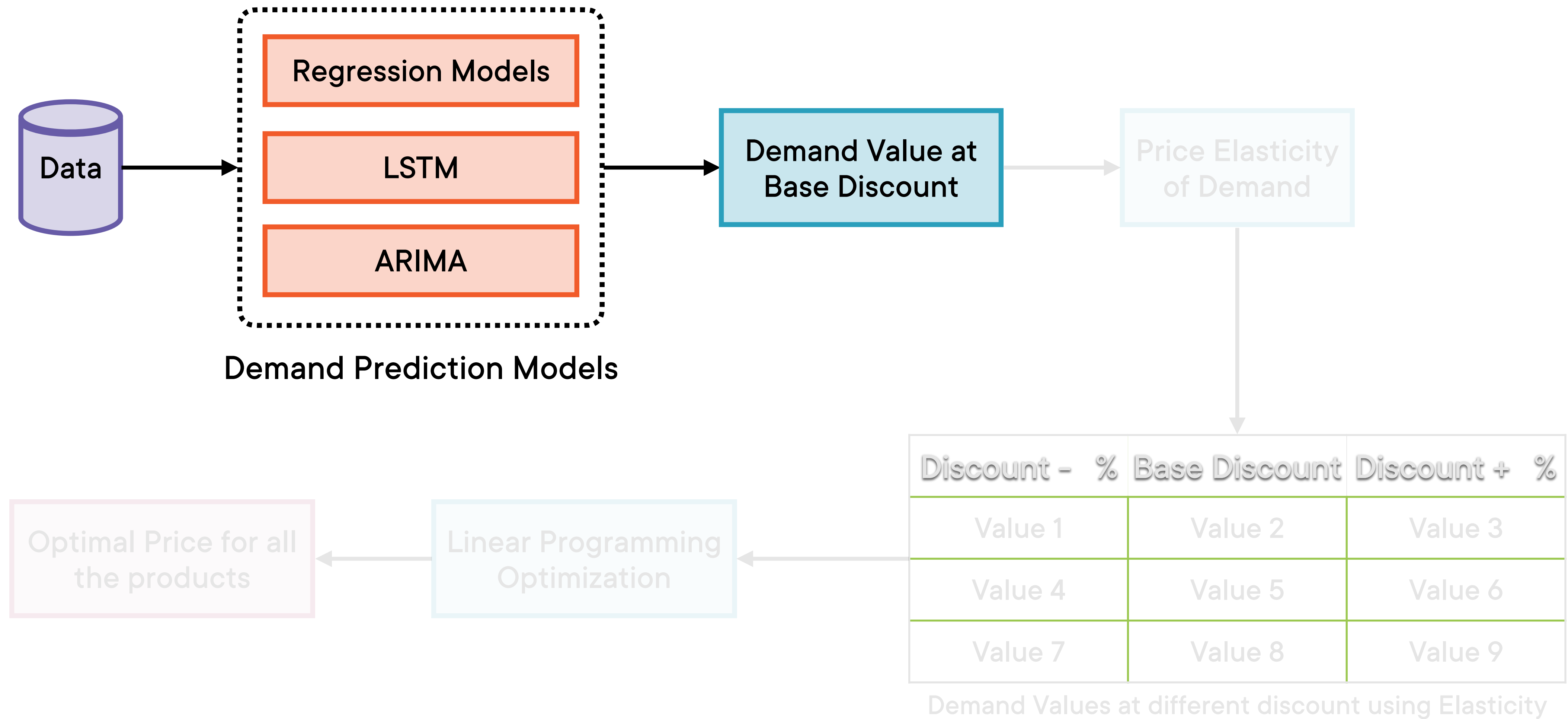
Feature Engineering



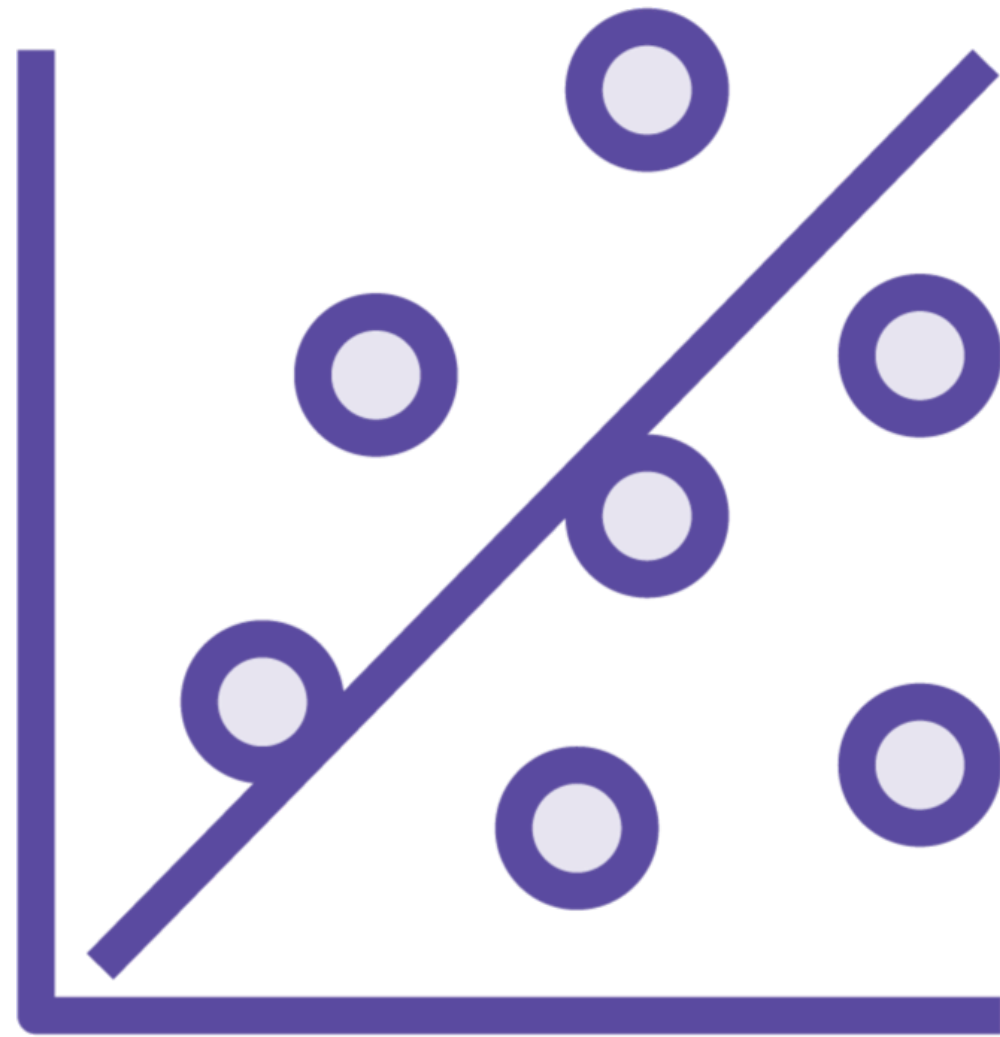
Feature Engineering



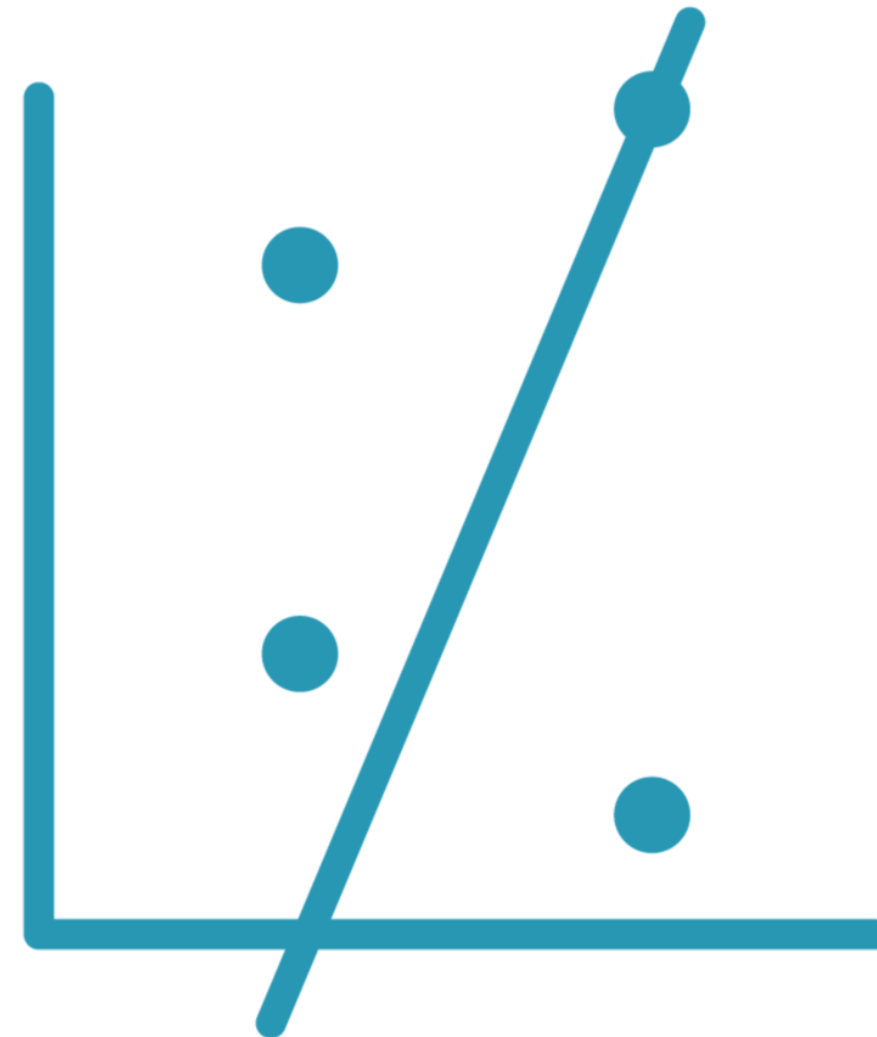
Price Optimization Workflow



Demand Prediction Model



Regression models

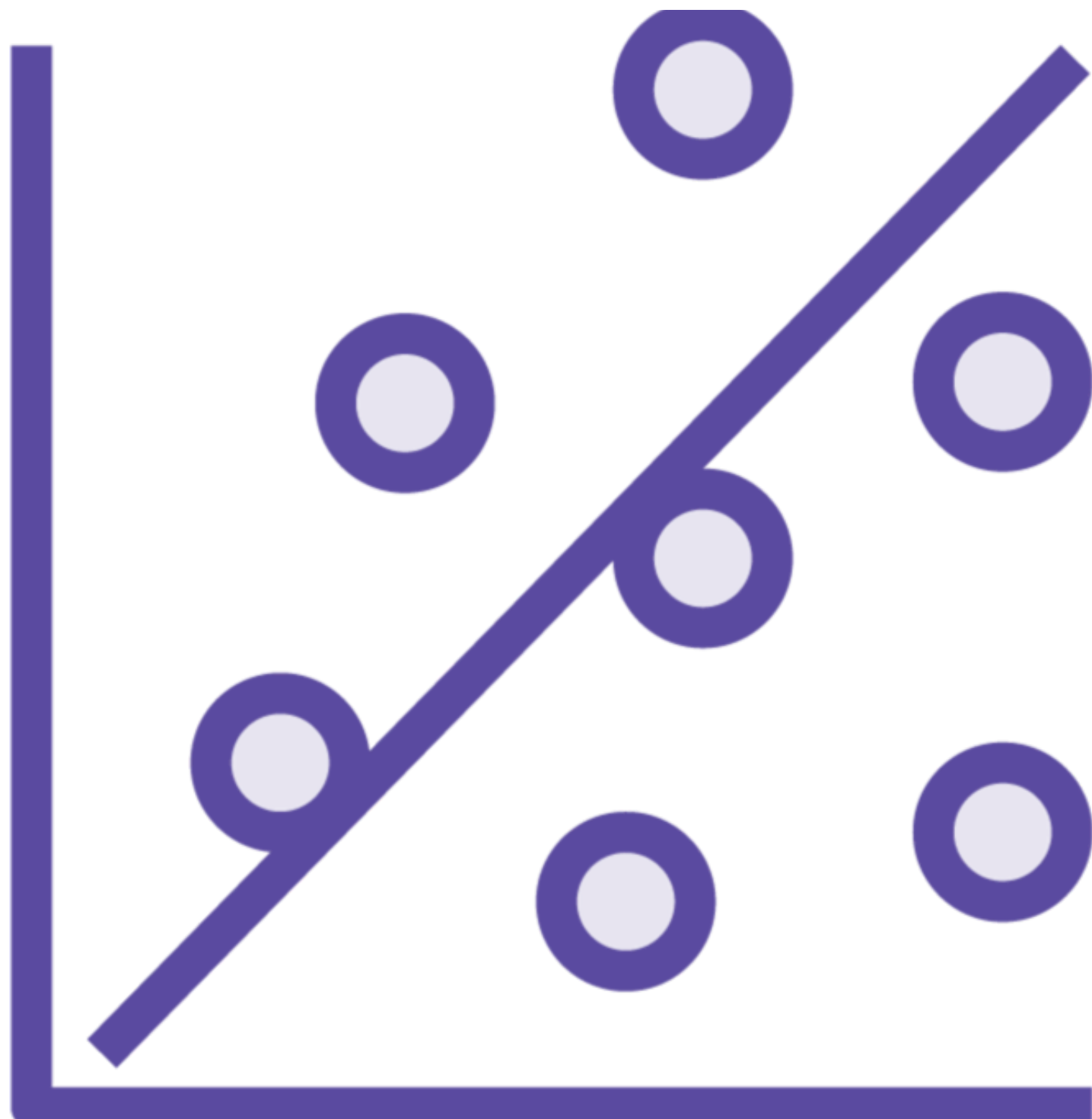


ARIMA



**Sequence model
with LSTM**

Regression Models



Linear regression

Random forest

XGBoost

MLP Regressor

Ensemble of all models specified above

ARIMA Model

Class of statistical models for analyzing and forecasting time series data

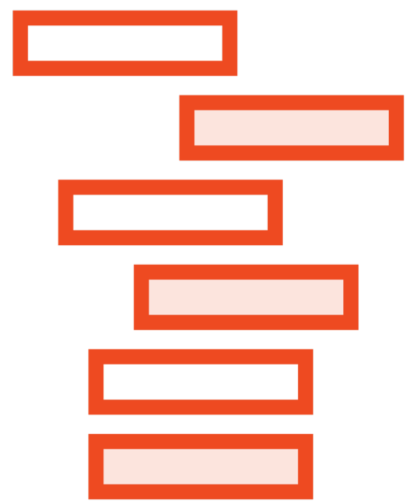
ARIMA Model

AutoRegressive Integrated Moving Average

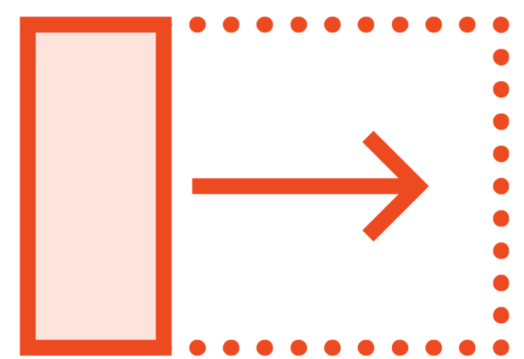
ARIMA Model



Autoregression: A model that uses the dependent relationship between an observation and some number of lagged observations



Integrated: Subtracting an observation from an observation at previous time step to make the time series **stationary**



Moving Average: Uses the dependency between an observation and a residual error from a moving average model applied to lagged observations

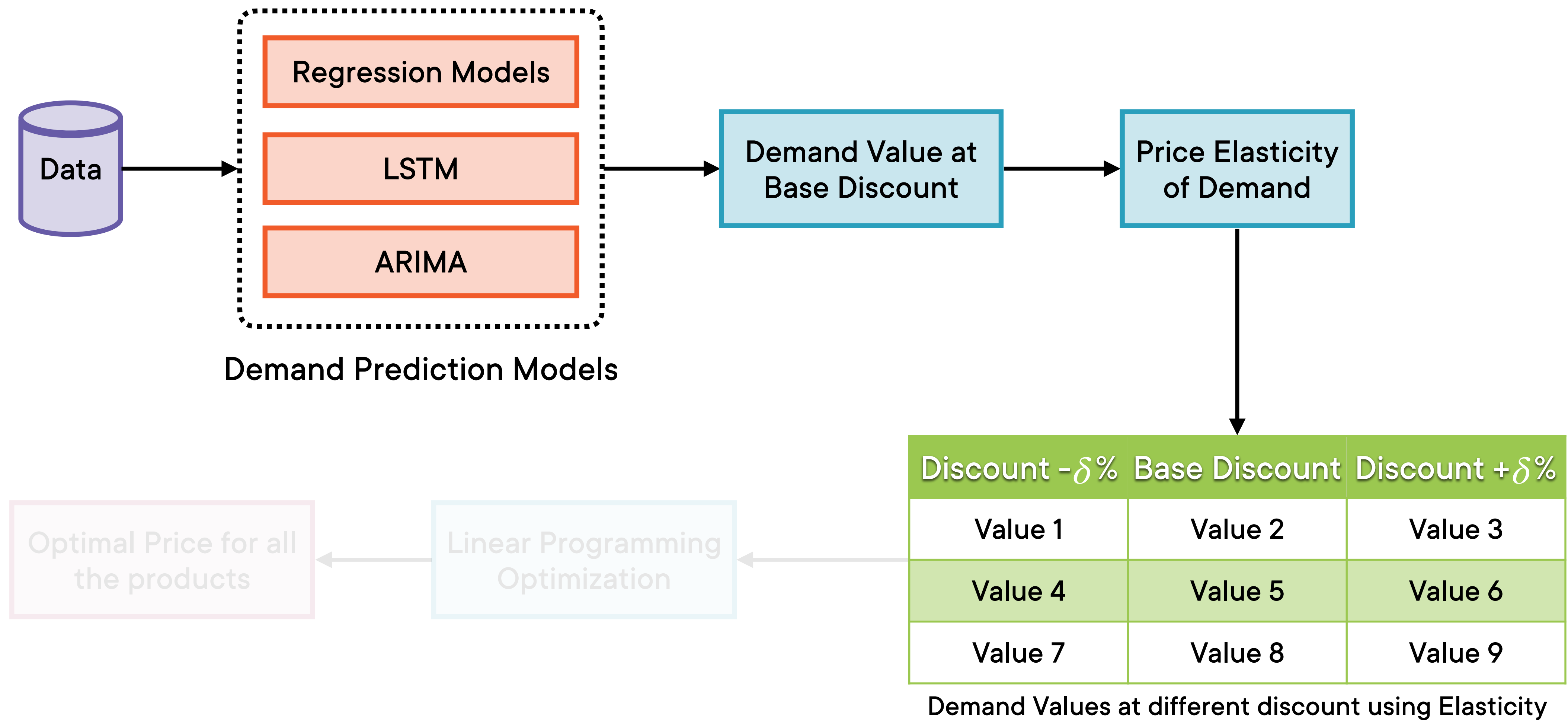
LSTM RNNs



Recurrent Neural Networks (RNNs) a sequential model that performs well on time series data

LSTM or Long Short Term Memory cells improve the performance of RNNs

Price Optimization Workflow



Price Elasticity of Demand

Price elasticity of demand is a measure of the change in the quantity purchased of a product in relation to a change in its price.

Price Elasticity of Demand



Individual products display different kinds of price elasticity

Price elasticity cannot be computed at a brand, category, or a global level

Computed for each product individually

Based on historical price-demand pairs for the product

Price Elasticity of Demand



**Demand value at base discount price
available from demand prediction model**

Use a discount threshold of $d\%$

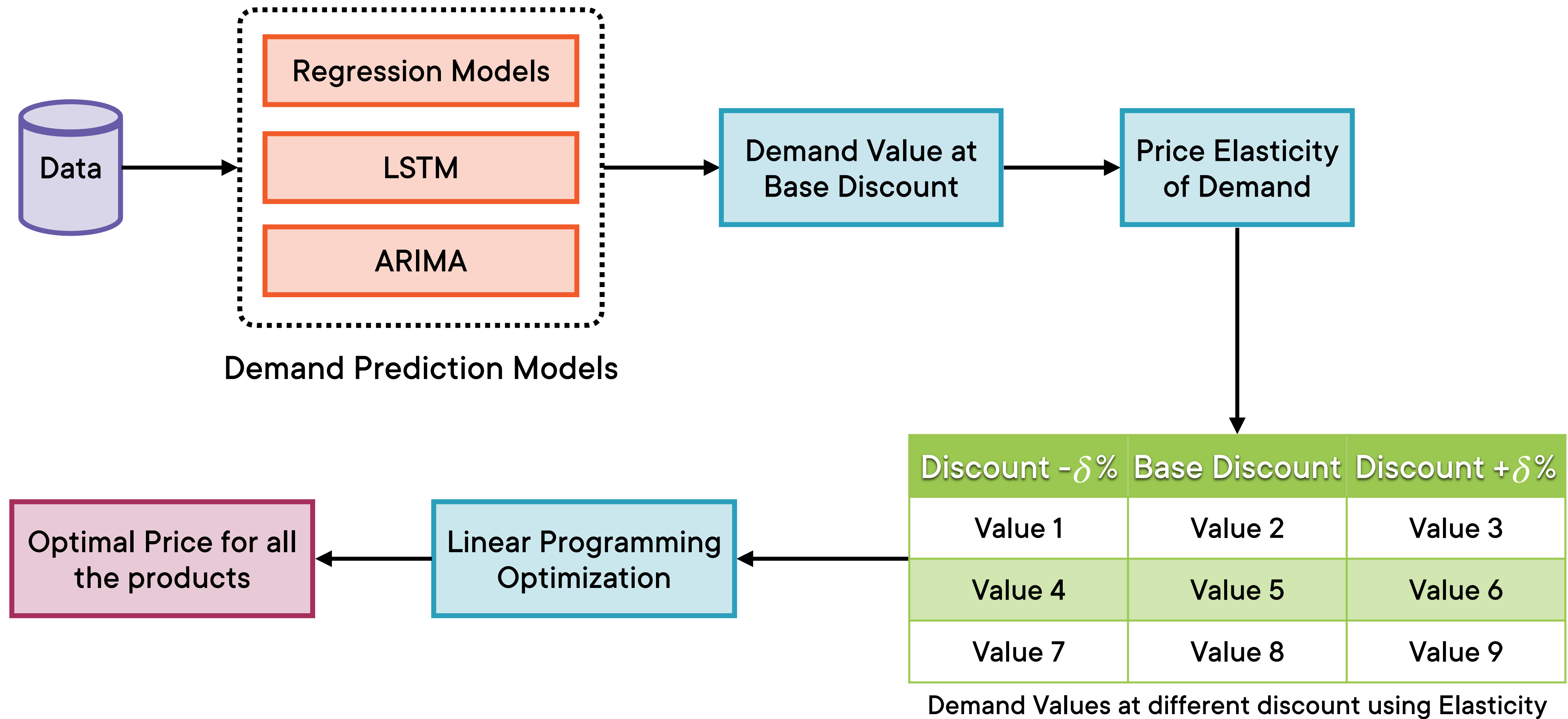
Compute 2 more demand values:

Base discount + $d\%$

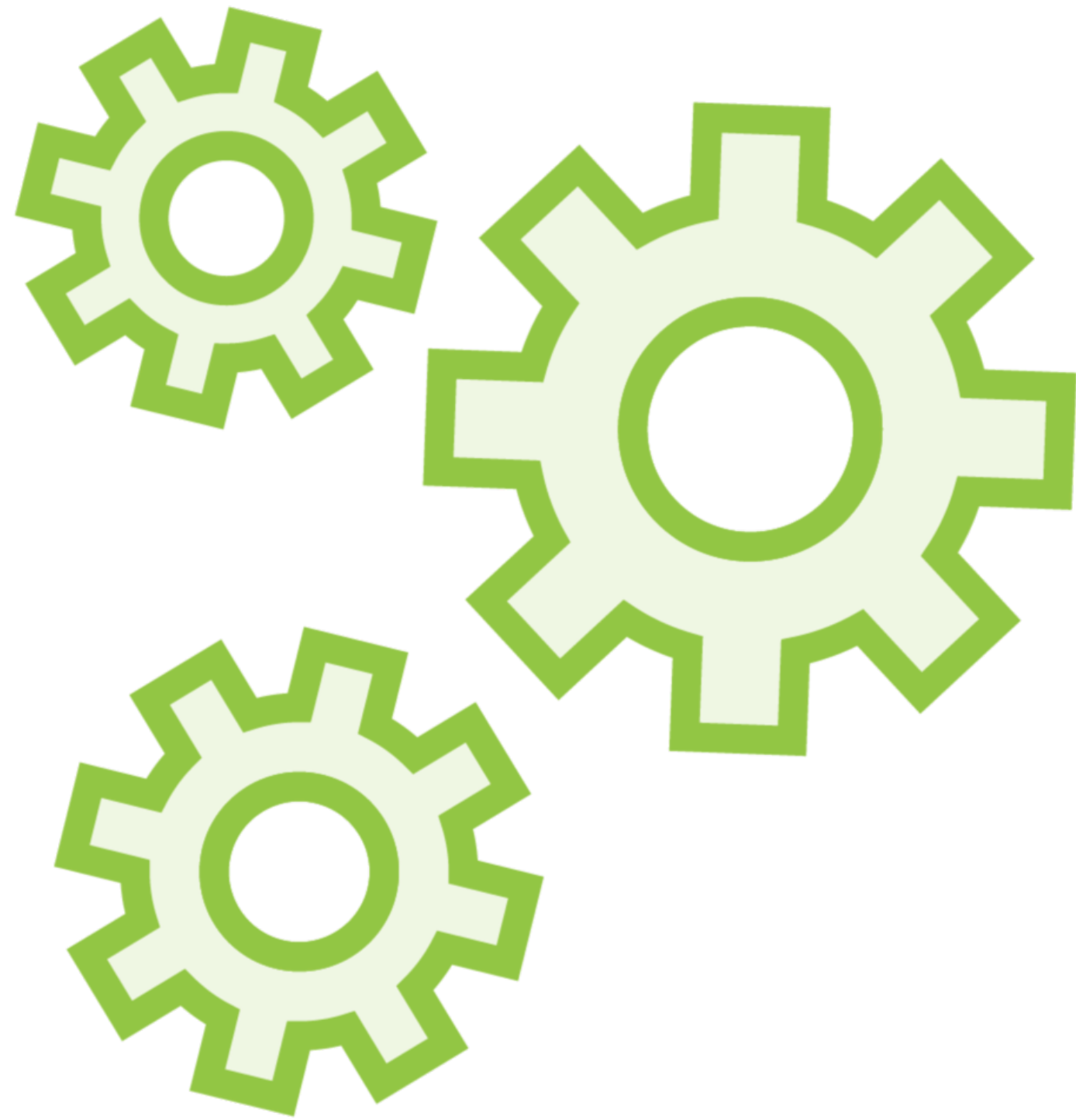
Base discount - $d\%$

**Total of 3 price points and 3 demand
values for each product**

Price Optimization Workflow



Linear Programming



Need to choose one of 3 prices for each product

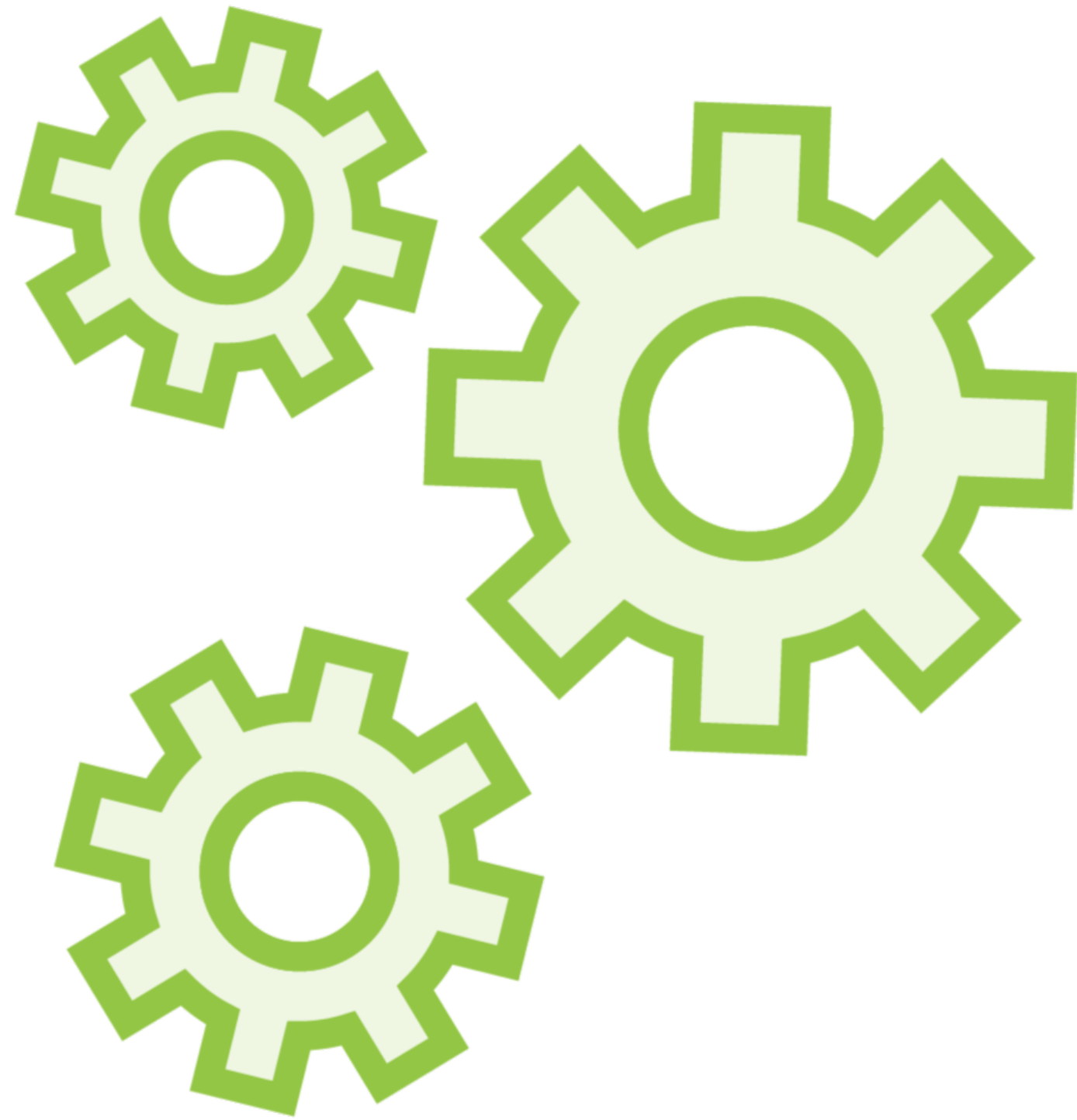
3 price points and N products = 3^N options

Price points are discrete values not continuous

Integer programming problem

Integer programming problems
very hard to solve – formulation
proved computationally intractable

Linear Programming



**Problem made tractable by reducing to
a linear programming problem**

Used Scipy to solve problem

A/B Testing



To test hypothesis that model prices are better than baseline prices

Set A - Control group shown baseline prices

Set B - Treatment group shown model prices

Percentage Increment in Revenue

	<i>Percentage increment in Revenue</i>	<i>GM % Uplift</i>
<i>Test 1</i>	0.96%	0.99%
<i>Test 2</i>	1.96%	0.95%
<i>Test 3</i>	0.09%	0.49%
<i>Test 4</i>	3.27%	-0.41%
<i>Test 5</i>	7.05%	0.15%

Different Categories of Products

	<i>Percentage increment in Revenue</i>	<i>GM % Uplift</i>
<i>Test 1</i>	0.96%	0.99%
<i>Test 2</i>	1.96%	0.95%
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Impact on Revenue

	<i>Percentage increment in Revenue</i>	<i>GM % Uplift</i>
<i>Test 1</i>	0.96%	0.99%
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<i>Test 5</i>	7.05%	0.15%

Impact on Gross Margin

	<i>Percentage increment in Revenue</i>	<i>GM % Uplift</i>
<i>Test 1</i>	0.96%	0.99%
<i>Test 2</i>	1.96%	0.95%
<i>Test 3</i>	0.09%	0.49%
<i>Test 4</i>	3.27%	-0.41%
<i>Test 5</i>	7.05%	0.15%

Approximately 1% increase in
revenue of the platform and 0.81%
uplift in gross margin due to model
recommended prices

Summary

Price elasticity of demand

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Fashion E-commerce**

Up Next:

Case Study: Optimizing Supply Planning
Using Machine Learning
