Lecture 10
Introduction to Machine Learning

1 What is Machine Learning?

2 A Controversy in the Wine World

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Pros: The model is super interpretable!
Cons: For complex tasks, there are too many rules, and we can’t anticipate them all.

What is Machine Learning?

Exercise: Pair up with the person sitting next to you. One of you will be an Earthling, the other a Martian.

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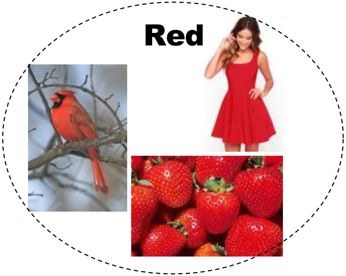
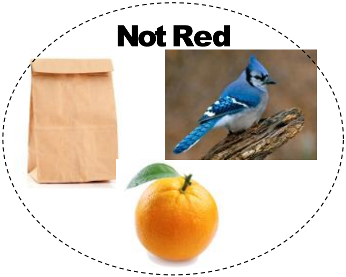
Moral: We often learn by seeing examples.





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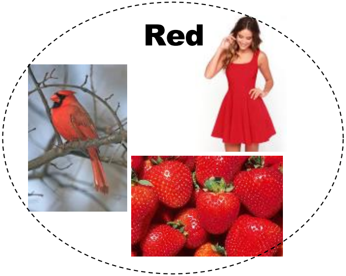

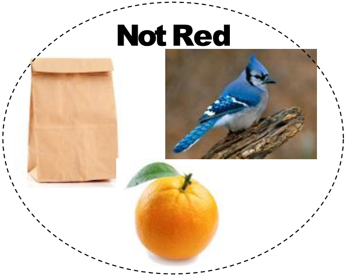

Rather than trying to come up with the rules ourselves, we can learn the rules from data. This is the essence of **machine learning**.

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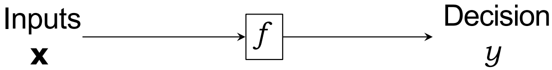

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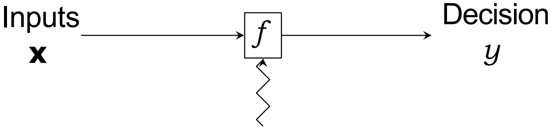

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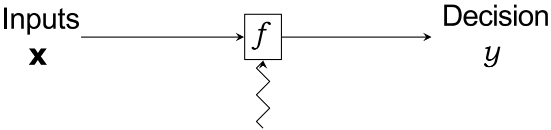

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The decision y is typically called the **target** or the **label**.

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Robert Parker

The Wine Advocate

The Wine Advocate is a famous wine-rating magazine founded by Robert Parker.

Robert Parker
The Wine Advocate

Orley Ashenfelter
Economics Professor

Robert Parker
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Orley Ashenfelter
Economics Professor

He is an American economics professor known for applying economics and statistical models to unusual topics such as wine quality prediction.

In 1991, Orley Ashenfelter predicted that the 1986 vintage of Bordeaux wines would be disappointing.

1986 Bordeaux şarap rekoltesi

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Robert Parker had predicted that the 1986 vintage would be "very good and some-times exceptional" based on tasting an early sample.

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1953	63.0	16.7	80	17.3	690	39
1955	45.0	17.1	130	16.8	502	37
1957	22.0	16.1	110	16.2	420	35
...	...	...	...	...	...	...
1988	NaN	17.1	59	16.8	808	4
1989	NaN	18.6	82	18.4	443	3
1990	NaN	18.7	80	19.3	468	2
1991	NaN	17.7	183	20.4	570	1

38 rows × 6 columns

summer – Average summer temperature (°C). Affects grape ripening and wine quality.
har (harvest rainfall) – Rainfall during harvest (mm). Too much rain can reduce quality.
sep – Average September temperature (°C). Important for final grape ripening.
win (winter rainfall) – Winter rainfall (mm). Influences soil water and vine growth.
age – Age of the wine (years). Older wines are usually more valuable.

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$$\mathbf{x} \longrightarrow \boxed{f} \longrightarrow y$$

summer temp,

winter rainfall,

harvest rainfall, age

price

Visualizing the Data

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import plotly.express as px

px.scatter(df[~df["price"].isnull()],
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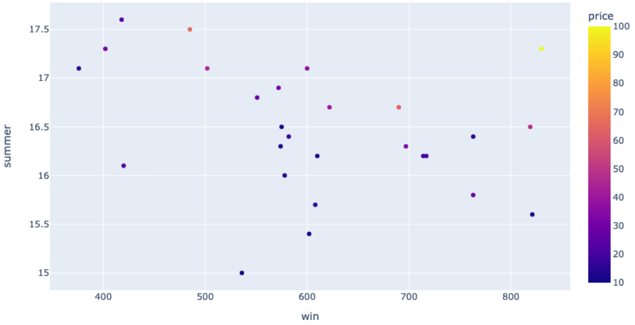

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import plotly.graph_objects as go

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fig2 = px.scatter(df[df["price"].isnull()],
                  x="win",  y="summer",  symbol_sequence=["circle-open"])

go.Figure(data=fig1.data + fig2.data, layout=fig1.layout)
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plotly.express (px) = fast and easy way to create

plotsplotly.graph_objects (go) = more detailed, low-level, and highly customizable plotting

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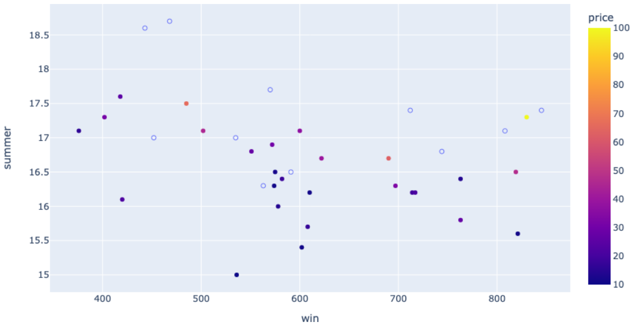

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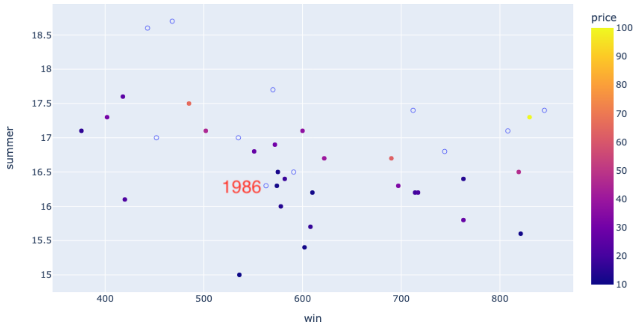

What would you predict is the quality of the 1986 wine?

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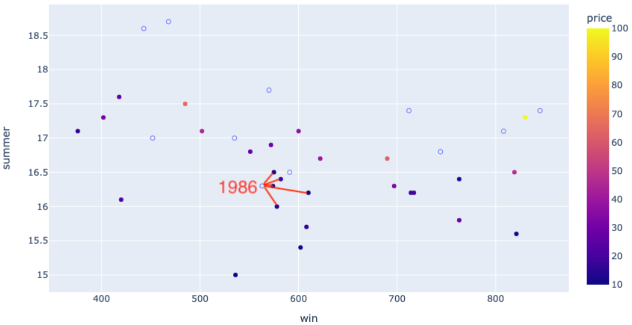

Insight: The “closest” wines are low quality, so the 1986 vintage is probably low quality as well.

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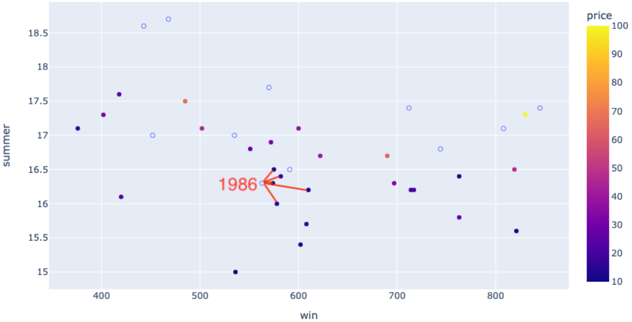

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This is the intuition behind k-**nearest neighbors**.

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The goal is to predict wine price (a regression problem.)

Note that the input features $\mathbf{x}$ may be categorical, quantitative, textual, …, or any combination of these.

Classification predicts categories or labels (e.g., good/bad, high/low).
Ashenfelter's model predicts an exact price or quality measure, not a class.