

Artificial Intelligence Foundation – JC3001

Lecture 38: Machine Learning – Regression I

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Material adapted from:

Russell and Norvig (AIMA Book): Chapter 19 (19.4–19.6)

Sebastian Thrun (Stanford University / Udacity)

Andrew Ng (Stanford University / Coursera)

Course Progression

- Part 1: Introduction
 - ① Introduction to AI ✓
 - ② Agents ✓
- Part 2: Problem-solving
 - ① Search 1: Uninformed Search ✓
 - ② Search 2: Heuristic Search ✓
 - ③ Search 3: Local Search ✓
 - ④ Search 4: Adversarial Search ✓
- Part 3: Reasoning and Uncertainty
 - ① Reasoning 1: Constraint Satisfaction ✓
 - ② Reasoning 2: Logic and Inference ✓
 - ③ Probabilistic Reasoning 1: BNs ✓
 - ④ Probabilistic Reasoning 2: HMMs ✓
- Part 4: Planning
 - ① Planning 1: Intro and Formalism ✓
 - ② Planning 2: Algorithms & Heuristics ✓
 - ③ Planning 3: Hierarchical Planning ✓
 - ④ Planning 4: Stochastic Planning ✓
- Part 5: Learning
 - ① Learning 1: Intro to ML ✓
 - ② **Learning 2: Regression**
 - ③ Learning 3: Neural Networks
 - ④ Learning 4: Reinforcement Learning
- Part 6: Conclusion
 - ① Ethical Issues in AI
 - ② Conclusions and Discussion

Objectives

- Regression Problems
- Gradient Algorithms
- Linear Regression
- Linear Classifiers



Outline

1 Recap

► Recap

► Linear Regression

► Hypothesis Representation

We learned the basic terminology for machine learning:

- Types of machine learning models:
 - Supervised Learning
 - Unsupervised Learning
 - Reinforcement Learning
- Supervised learning tasks
 - Classification
 - Regression
- Issues with Machine Learning

And studied one simple, but powerful, machine learning model: Decision Trees



Outline

2 Linear Regression

► Recap

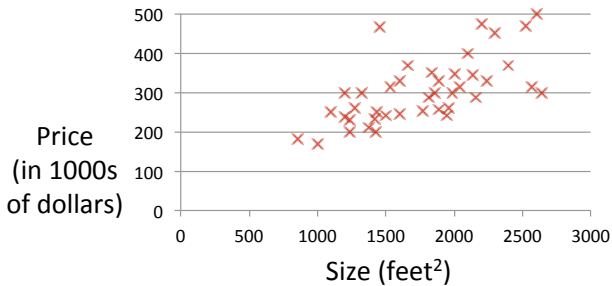
► Linear Regression

► Hypothesis Representation

House Prices (Portland, OR)

Supervised Learning Example

2 Linear Regression

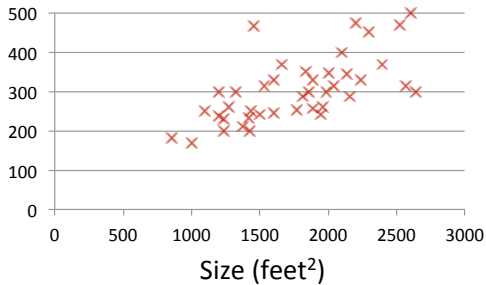


House Prices (Portland, OR)

Price
(in 1000s
of dollars)

Supervised Learning Example

2 Linear Regression



Supervised Learning

Given the “right answer” for each example in the data.

Regression Problem

Predict real-valued output

Training Example and Notation

2 Linear Regression

**Training Set of
House Prices
(Portland, OR)**

Size in feet ² (x)	Price (\$) in 1000's (y)
2104	460
1416	232
1534	315
852	178

Training Example and Notation

2 Linear Regression

**Training Set of
House Prices
(Portland, OR)**

Size in feet ² (x)	Price (\$) in 1000's (y)
2104	460
1416	232
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Notation:

m = Number of training examples

x 's = "input" variable / features

y 's = "output" variable / "target" variable

Training Example and Notation

2 Linear Regression

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(x, y) – one training example

$(x^{(i)}, y^{(i)})$ – i^{th} training example

Training Example and Notation

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$x^{(1)} = 2104$

Training Example and Notation

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$x^{(2)} = 1416$

Training Example and Notation

2 Linear Regression

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Outline

3 Hypothesis Representation

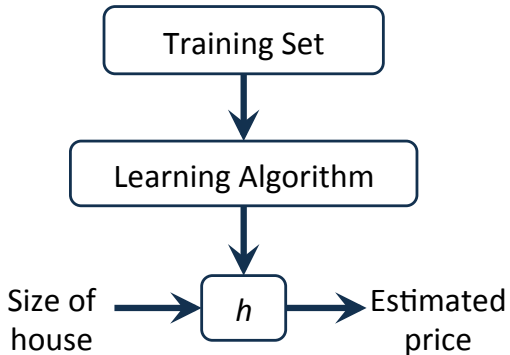
► Recap

► Linear Regression

► Hypothesis Representation

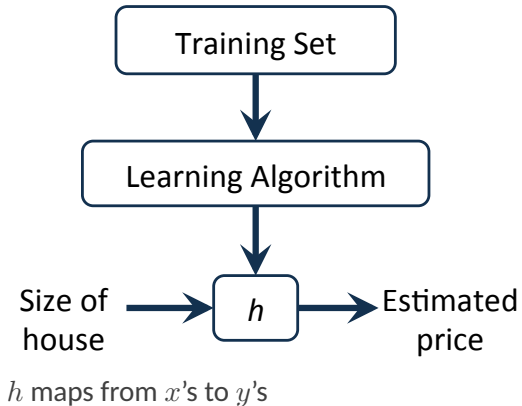
Hypothesis Representation

3 Hypothesis Representation



Hypothesis Representation

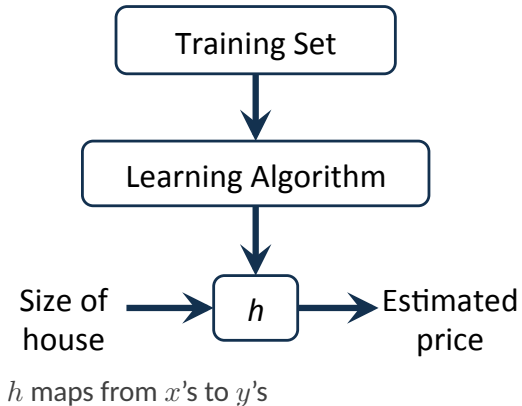
3 Hypothesis Representation



Hypothesis Representation

3 Hypothesis Representation

How do we represent h ?



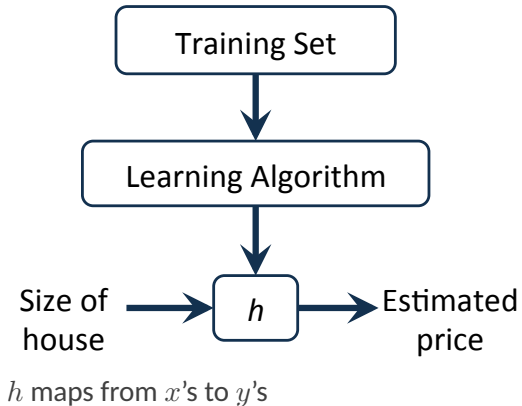
Hypothesis Representation

3 Hypothesis Representation

How do we represent h ?

$$h_w(x) = w_0 + w_1x$$

Shorthand: $h(x)$



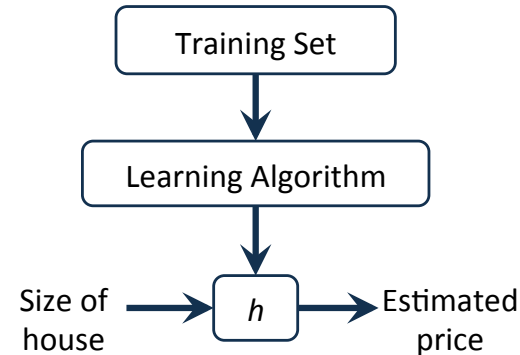
Hypothesis Representation

3 Hypothesis Representation

How do we represent h ?

$$h_{\mathbf{w}}(x) = \mathbf{w}_0 + \mathbf{w}_1 x$$

Shorthand: $h(x)$



h maps from x 's to y 's

Linear regression with one variable (x)

Univariate linear regression

Choosing w s

3 Hypothesis Representation

	Size in feet ² (x)	Price (\$) in 1000's (y)
Training Set	2104	460
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Hypothesis: $h_w(x) = w_0 + w_1x$

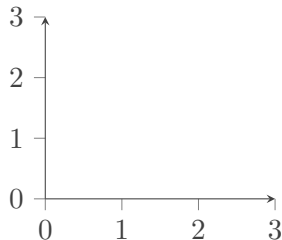
w_i 's: Parameters

How to choose w_i 's?

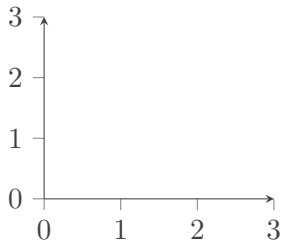
Hypothesis Example

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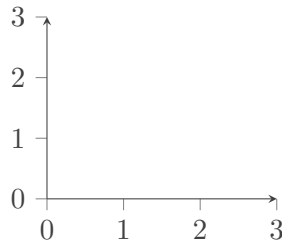
$$h_w(x) = w_0 + w_1x$$



$$w_0 = 1.5$$
$$w_1 = 0$$



$$w_0 = 0$$
$$w_1 = 0.5$$

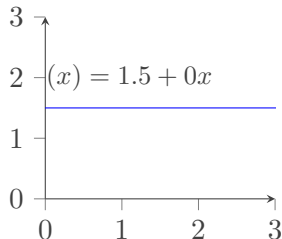


$$w_0 = 1$$
$$w_1 = 0.5$$

Hypothesis Example

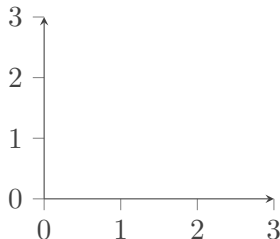
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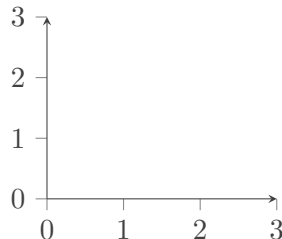
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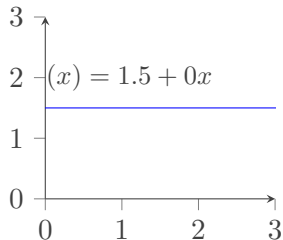
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Hypothesis Example

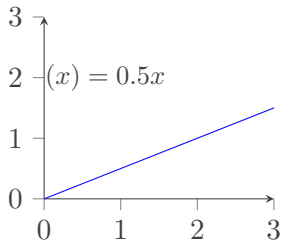
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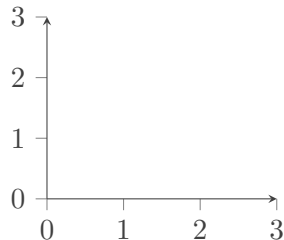
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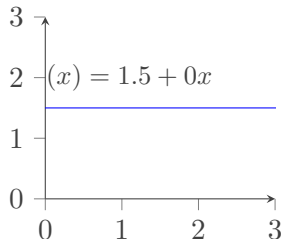
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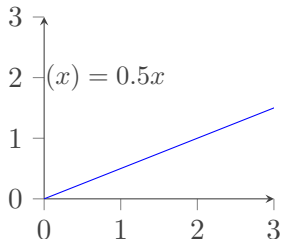
Hypothesis Example

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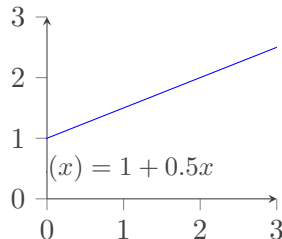
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To continue in the next session.