CS 474/574 Machine Learning
1. Introduction

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- The first approach in the context of AI is also called rule-based system or expert system, e.g. MyCin, Grammarly.

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- It is a dream. "Creating an artificial being has been the dream since the beginning of science." – Movie A.I., Spielberg et al., 2001

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In[1]:= EdgeDetect[

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Out[1]=

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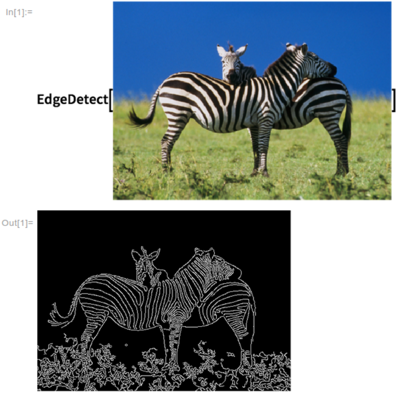

- Another example in machine translation

Supervised ML as function approximation

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- Reinforcement, let the machine find ground truth itself

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- If x involves categorical values (e.g., gender), there are usually two approaches: **One-hot encoding** and **embedding** (in DL context, to be discussed later).

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- Classification vs. Regression: When y is continuous or discrete. In modern DL context, such division is usually no mentioned, expecially in generative tasks.