Feature Construction for Linear Methods

Objectives

☐ Describe Coarse Coding

☐ Describe how Coarse coding relates to state aggregation

☐ Understand how discrimination and generalization affects learning accuracy
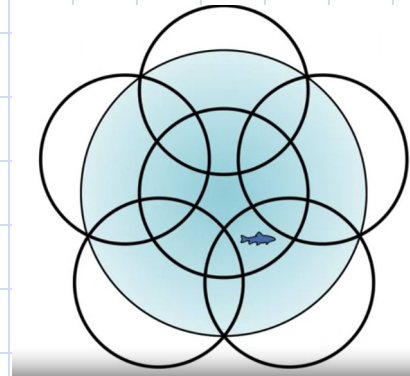
☐ Describe Tile Coding

Coarse Coding

□ State aggregation does not usually allow the shapes to overlap.

□ By allowing overlap, we obtain a more flexible class of feature representations called course c
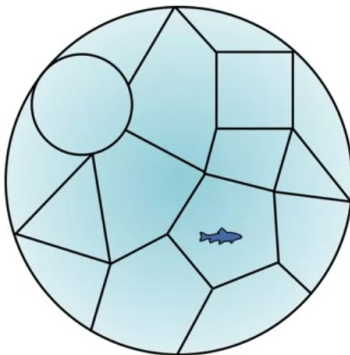
State aggregation

Coarse Coding

Coarse Coding

- ☐ Coarse coding provides an effective way to represent high-dimensional state spaces in reinforcement learning, allowing for efficient function approximation and learning in complex environments.

- ☐ It strikes a balance between discretization and generalization, enabling agents to learn and make decisions effectively in large state spaces.

Feature Construction for Linear Methods

Coarse Coding

☐ The example feature vector for the fishes current location in the pond.

☐ Each index in the feature vector corresponds to one of the shapes.

☐ The feature corresponding to the circle is active or set to 1 if the fish is within that circle, otherwise the feature set to 0.
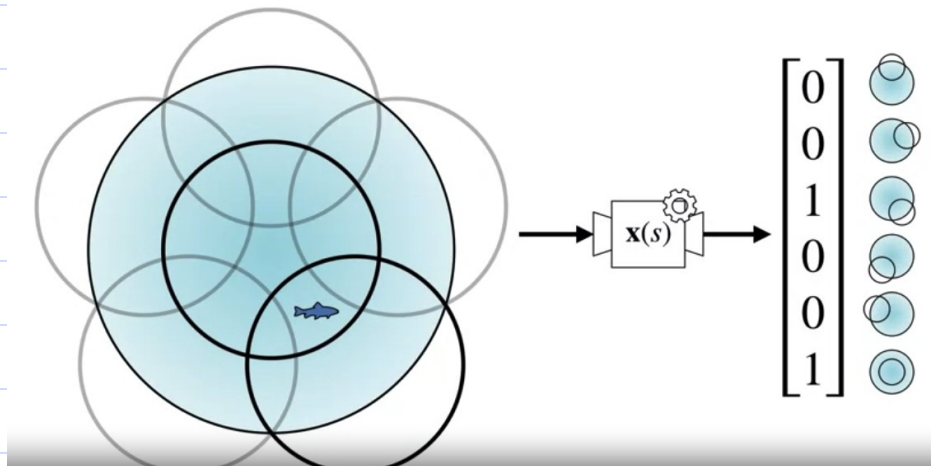
Coarse Coding

☐ The example, the fishes current location in the pond.

  ☐ The features receptive field corresponds to the locations that activate that feature.

  ☐ When the fish moves to a new location, it's usually covered by a different set of circles.

  ☐ Nearby states will have similar feature activations, but they may also have different components active including different numb
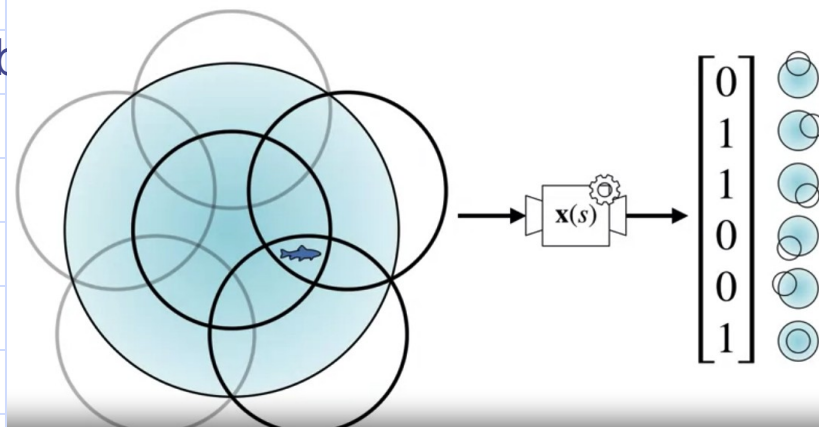
Discrimination and Generalization

□ They important roles in learning accuracy, and finding the right balance

□ Discrimination helps capture fine-grained distinctions in the data.

□ Generalization ensures that the model can make accurate predictions or decisions in diverse and unseen situations.

Discrimination affect Learning Accuracy

❑ Definition:

  ❑ Discrimination refers to the ability of a learning algorithm to distinguish between different classes or states in the training data.

  ❑ It involves learning fine-grained distinctions and capturing specific patterns or features unique to each class or state.

Discrimination affect Learning Accuracy

☐ Effect on Learning Accuracy:

  ☐ Discrimination can improve learning accuracy in situations where fine-grained distinctions are crucial for making accurate predictions or decisions.

  ☐ Discriminatory models can achieve high accuracy on tasks that require precise classification or prediction.

Discrimination affect Learning Accuracy

☐ Risk of Overfitting:

    ☐ However, excessive discrimination can lead to overfitting, where the model memorizes noise or irrelevant details in the training data, resulting in poor generalization performance on unseen data.

    ☐ This can reduce overall learning accuracy, especially in noisy or complex environments.

Generalization affect Learning Accuracy

□ Definition:

　□ Generalization refers to the ability of a learning algorithm to perform well on unseen data or in new situations beyond the training data.

　□ It involves capturing underlying patterns and relationships in the data that are consistent across different instances or contexts.

Generalization affect Learning Accuracy

☐ Effect on Learning Accuracy:

　☐ Generalization is essential for achieving high learning accuracy in real-world applications.

　☐ Models that generalize well can effectively capture the underlying structure of the data and make reliable predictions even in novel situations.

Generalization affect Learning Accuracy

□ Risk of Underfitting:

    □ Excessive generalization can lead to underfitting, where the model fails to capture important patterns or variations in the data, resulting in poor performance even on the training data.

    □ This can also reduce learning accuracy, especially if the model oversimplifies the underlying relationships in the data.

Tile Coding

❑ It is a technique used in reinforcement learning and function approximation to represent high-dimensional state spaces more efficiently.

❑ It involves dividing the continuous state space into a set of overlapping tiles or regions and encoding the presence or absence of the state within each tile.

Tile Coding

□ Tile Partitioning:

  □ The continuous state space is divided into a set of non-overlapping tiles or regions. These tiles collectively cover the entire state space, and each state falls within one or more tiles.

□ Encoding Scheme:

  □ Each tile is assigned a unique identifier or code, which is used to represent the presence or absence of the state within that tile

Tile Coding

☐ Overlapping Tiles:

☐ To capture correlations and interactions between adjacent states, tiles are typically allowed to overlap.

☐ Feature Vector Representation:

☐ The state is represented as a feature vector, where each element of the vector corresponds to a tile or region in the tile coding scheme.

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Tile Coding

❑ Efficient Function Approximation:

   ❑ Tile coding allows for efficient function approximation using simple linear models or neural networks.

   ❑ Instead of directly approximating the value function or policy over the continuous state space, the function approximator learns to predict values or policies based on the tile-coded feature vector representation of states.

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Tile Coding

□ Generalization and Compression:

    □ Despite the coarse granularity of the tiles, tile coding enables generalization across similar states within each tile.

    □ By representing multiple similar states with the same tile-coded feature vector, tile coding achieves compression of the state space while preserving important state information.

Tile Coding

□ Training and Learning:

- □ Tile-coded feature vectors are used as input to the function approximator, which is trained using reinforcement learning algorithms such as TD learning, Q-learning, or policy gradient methods.

- □ The function approximator learns to associate each tile-coded state representation with its corresponding value or policy.

Using Tile Coding in TD

☐ Using tile coding in TD learning involves leveraging tile-coded feature representations of states to estimate value functions or policies more efficiently.

☐ Agents can efficiently learn value functions or policies in high-dimensional state spaces, achieving a balance between granularity and generalization while effectively representing the environment's dynamics.

Using Tile Coding in TD

❑ This approach is particularly useful in real-world reinforcement learning tasks with complex and continuous state spaces.

Summary

☐ Describe Coarse Coding

☐ Describe how Coarse coding relates to state aggregation

☐ Understand how discrimination and generalization affects learning accuracy

☐ Describe Tile Coding

Q & A

Feature Construction for Linear Methods