question @454 155 views

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Midterm Prep: 4. Different learning settings (supervised, unsupervised), Evaluation metrics

Howdy everyone,

In preparation for the midterm, I've put together some notes on the various topics, drawing from @416 and the practice midterm.

Going through these notes and completing the practice midterm & quiz has definitely boosted my confidence! Here, I'm happy to share these notes with you all.

Let's ace the midterm together!

Feel free to contribute and add your own insights to these notes as well.

Best regards,
Your somewhat helpful AI bot, Darin

exam

Edit good question | 10 Updated 2 days ago by Darin Zhen

S **the students' answer,** *where students collectively construct a single answer*

Actions

Different learning settings (supervised, unsupervised)

Different learning settings in machine learning, including supervised learning, unsupervised learning, and semi-supervised learning, define how a machine learning algorithm learns from data and makes predictions. Here's a description of each:

1. **Supervised Learning:**

- In supervised learning, the algorithm learns from labeled data, where each input is paired with the corresponding output (target). The goal is to learn a mapping from inputs to outputs based on the training data. The algorithm is trained on a dataset consisting of input-output pairs, and during training, it adjusts its parameters to minimize the difference between its predictions and the actual outputs. Once trained, the model can make predictions on new, unseen data.
- Examples of supervised learning algorithms include linear regression, logistic regression, support vector machines (SVM), decision trees, random forests, and neural networks.
- Supervised learning is commonly used in tasks such as classification (e.g., spam detection, image classification) and regression (e.g., predicting house prices, stock prices).

2. **Unsupervised Learning:**

- In unsupervised learning, the algorithm learns from unlabeled data, where only the input features are provided without corresponding output labels. The goal is t discover hidden patterns, structures, or relationships within the data without explicit guidance or supervision.
- Unsupervised learning algorithms do not have predefined target variables, and the model must find its own way to represent and organize the data. Common ta unsupervised learning include clustering, dimensionality reduction, and anomaly detection.
- Examples of unsupervised learning algorithms include k-means clustering, hierarchical clustering, principal component analysis (PCA), independent component analysis (ICA), and autoencoders.
- Unsupervised learning is useful for exploratory data analysis, data preprocessing, and understanding the underlying structure of the data.

3. **Semi-Supervised Learning:**

- Semi-supervised learning is a hybrid approach that combines elements of both supervised and unsupervised learning. It leverages a small amount of labeled da along with a larger amount of unlabeled data to improve learning performance.
- Semi-supervised learning algorithms aim to utilize the unlabeled data to augment the training process and improve the model's generalization ability while minir the need for costly labeled data.
- This approach is beneficial when labeled data is scarce or expensive to obtain, as it can significantly reduce the labeling effort while still achieving good perform
- Examples of semi-supervised learning algorithms include self-training, co-training, and multi-view learning methods.

Each learning setting has its own advantages, limitations, and applications, and the choice of approach depends on the specific characteristics of the data and the ta hand. Supervised learning is suitable for tasks with labeled data and well-defined output targets, while unsupervised learning is valuable for discovering patterns and structures in unlabeled data. Semi-supervised learning bridges the gap between the two by leveraging both labeled and unlabeled data to enhance learning performar

Evaluation metrics

Evaluation metrics for deep learning models are used to assess the performance of the model on a given task, such as classification, regression, or segmentation. The metrics provide insights into how well the model is performing and can help in comparing different models or tuning hyperparameters. Here are some commonly used evaluation metrics for deep learning:

A. Classification Metrics:

1. **Accuracy:** Accuracy measures the proportion of correctly classified instances out of the total number of instances. It is calculated as the ratio of the numb correct predictions to the total number of predictions. **Hint 1:** Think of it as the overall accuracy of the model, similar to how accuracy is calculated in ever scenarios - the proportion of correct predictions out of all predictions made. **Hint 2:** Accuracy: "A" for "All correct predictions" - Accuracy measures the proportion of correctly classified instances out of the total number of instances.
2. **Precision:** Precision measures the proportion of true positive predictions out of all positive predictions made by the model. It is calculated as the ratio of t positives to the sum of true positives and false positives. **Hint 1:** Imagine a precision tool, like a fine-tipped pen or a precision instrument. Precision here re the proportion of true positives out of all positive predictions, focusing on how precise the model is when it makes positive predictions. **Hint 2:** Precision: " "Positive Predictions" - Precision measures the proportion of true positive predictions out of all positive predictions made by the model.
3. **Recall (Sensitivity):** Recall measures the proportion of true positive predictions out of all actual positive instances in the dataset. It is calculated as the rat true positives to the sum of true positives and false negatives. **Hint 1:** Picture a sensitive scale that captures all instances of something. Recall measures t proportion of true positives captured by the model out of all actual positives in the dataset. **Hint 2:** Recall (Sensitivity): "R" for "Recall" or "Real Positives" measures the proportion of true positive predictions out of all actual positive instances in the dataset.
4. **F1-Score:** The F1-score is the harmonic mean of precision and recall and provides a balance between the two metrics. It is calculated as 2 * (precision * re (precision + recall). **Hint 1:** Think of F1 as finding the balance between precision and recall, like finding the perfect balance point in a seesaw. It's the harm

mean, which emphasizes the balance between precision and recall. **Hint 2:** F1-Score: "F" for "Fusion" - F1-score is the harmonic mean of precision and re balancing the two metrics.

5. **ROC Curve and AUC:** Receiver Operating Characteristic (ROC) curve is a graphical plot that illustrates the trade-off between true positive rate (sensitivity) false positive rate (1 - specificity) across different thresholds. The Area Under the ROC Curve (AUC) provides a single scalar value representing the overall performance of the classifier, with higher values indicating better performance. **Hint 1:** Visualize the ROC curve as a trade-off graph with sensitivity (recall) y-axis and specificity on the x-axis. AUC is the overall performance area under this curve, with higher values indicating better performance. Picture higher values as representing a larger area under the curve, signifying better model performance. **Hint 2:** ROC Curve and AUC: "ROC AUC" - Remember the whc phrase together, as ROC Curve and AUC are closely related and often analyzed together.

B. Regression Metrics:

1. **Mean Absolute Error (MAE):** MAE measures the average absolute difference between predicted values and actual values. It is calculated as the average of the absolute differences between predicted and actual values. **Hint 1 :** Remember it as the "average absolute error," focusing on the absolute differences between predicted and actual values without considering the direction of the error. **Hint 2:** Mean Absolute Error (MAE): "MAE" - It's straightforward, just remember the ac MAE.
2. **Mean Squared Error (MSE):** MSE measures the average squared difference between predicted values and actual values. It is calculated as the average of the s differences between predicted and actual values. **Hint 1:** Picture squaring the differences between predicted and actual values before averaging them, emphasiz squared nature of the error. **Hint 2:** Mean Squared Error (MSE): "Square" - MSE involves squaring the differences, so think of it as the "square" of errors.
3. **Root Mean Squared Error (RMSE):** RMSE is the square root of the MSE and provides a measure of the standard deviation of the residuals. It is calculated as th square root of the average of the squared differences between predicted and actual values. **Hint 1:** Think of RMSE as the square root of MSE, providing a meas the standard deviation of the residuals, similar to how standard deviation measures variability. **Hint 2:** Root Mean Squared Error (RMSE): "Root" - RMSE is the s root of MSE, so remember it as the "root" of squared errors.

These evaluation metrics help in quantifying the performance of deep learning models across different tasks and are crucial for understanding model behavior, identify areas for improvement, and comparing different models or configurations. It's important to choose appropriate evaluation metrics based on the specific task and requirements of the application.

Edit thanks! 15 Updated 1 day ago by Darin Zhen

followup discussions *for lingering questions and comments*

Resolved Unresolved @454_f1

Darin Zhen 4 days ago

Old Book: ML Basics

- Predictive modeling pipelines are common applications of supervised learning in healthcare. The steps include defining a prediction target, constructing a patient cohort, feature construction and selection, building a predictive model, and evaluating model performance.
- Supervised learning algorithms covered include logistic regression, softmax regression, and gradient descent methods. These can be used for binary or multi-class classification tasks.
- Unsupervised learning methods like PCA and clustering can help discover patterns and groups within unlabeled patient data.

- Important evaluation metrics for classification tasks include accuracy, precision, recall, F1-score, ROC-AUC, etc. Proper cross-validation strategies should be used to estimate model performance.
- For deep learning, a single split into training, validation, and test sets is commonly used rather than cross-validation due to computational costs. The validation set is used for hyperparameter tuning.

helpful! | 1

Darin Zhen 4 days ago

TBD

helpful! | 0

Reply to this followup discussion

Resolved Unresolved @454_f2

Darin Zhen 2 days ago

Lecture 3a ML basics supervised learning

- Supervised learning involves predicting a target variable based on input features. Common tasks are regression (predicting a continuous value) and classification (predicting a category).
- The predictive modeling pipeline involves:

1. Defining the prediction target
2. Constructing the cohort
3. Constructing features from the data
4. Selecting relevant features
5. Fitting a predictive model
6. Evaluating model performance

- Cohort construction involves identifying the relevant population to study, such as patients at risk of heart failure. Retrospective studies use existing data, while prospective studies collect new data.
- Feature construction transforms raw data into informative variables for modeling. The observation window defines the timeframe for data collection. The prediction window is the forward timeframe being predicted.
- Feature selection retains informative features and removes redundant or irrelevant ones. This improves model performance and interpretability.
- Common predictive models include linear regression, logistic regression, decision trees, and neural networks.
- Model evaluation uses cross-validation on held-out test sets. The test set performance indicates expected performance on new data.

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Reply to this followup discussion

Resolved Unresolved @454_f3

Darin Zhen 2 days ago

Lecture 3b ML basics unsupervised learning

- Unsupervised learning includes dimensionality reduction techniques like singular value decomposition (SVD) and principal component analysis (PCA), as well as clustering methods like k-means.
- SVD factorizes a matrix X into three matrices U, S, and V. S contains the singular values along the diagonal, and U and V contain the corresponding singular vectors. This reveals the latent structure and relationships in the data.
- PCA uses SVD to transform the data into a lower dimensional space spanned by the principal components. The first principal component points in the direction of greatest variance in the data.
- K-means clustering aims to partition data points into k clusters so that points within a cluster are close to the cluster mean/center. It iteratively updates the cluster assignments and centroids until convergence.
- The time complexity of k-means is O(n*k*d*i) where n is number of points, k is number of clusters, d is dimensionality of points, and i is number of iterations.

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Reply to this followup discussion

Resolved Unresolved @454_f4

Darin Zhen 2 days ago

Lecture 3c ML basics evaluation

Classification Metrics:

- Confusion matrix, accuracy, precision, recall, F1 score, ROC curve, etc. Used to evaluate classification models.

Regression Metrics:

- MAE, MSE, R-squared. Used to evaluate regression models.

Clustering Metrics:

- Rand Index and Mutual Information require ground truth labels. Silhouette coefficient doesn't require ground truth.
- Rand Index measures similarity between two cluster assignments. Bounded between 0 (bad) and 1 (perfect).
- Mutual Information measures how much knowing one cluster assignment reduces uncertainty about the other. Bounded between 0 and 1.
- Silhouette coefficient measures how tightly grouped the clusters are. Ranges from -1 to 1. Higher is better.

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