Look at numpy from assignments. ✓

KNN ✓

Decision Trees

Stats

Linear Algebra.

Vectorization ✓

Use chatgpt to generate practice questions.

Look at SLIDES and ASSIGNMENTS

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KNN:

$\sqrt{1^2+1^2}=\sqrt{2}$

$\sqrt{2}$ 2 2

training data → Data used to train the model.
testing data → Data used to test the model.

Concept: Find k (usually odd number) nearest neighbors to test sample, pick majority class.

If k is even and split is equal, use weighted voting (closer = larger weight). Random?

Euclidean distance min dist $\sqrt{(x_1-x_0)^2+(y_1-y_0)^2}$

Possible edge cases in data:

- Ties in class labels.
- Noisy data
- High-dimensionality → curse of dimensionality.
- Imbalance in number of samples for a given class.
- Identical points.

overfits, all points appear equally close, distance metrics lose effectiveness high cost etc.

Training set = Test final model performance. Model doesn't see this while being trained.

Validation set = Use during training to tune hyper parameters

Tune hyper parameters using a validation set

Use test set at the very end to see generalization performance of the final configuration.

Choosing K

Small k
- Good at capturing patterns. (local structure)
- May overfit (be sensitive to noisy data)

Large k
- Stable predictions as it averages over lots of data.
- May under fit → As it smoothes, it fails to capture local patterns and ignores relevant/closer neighbors. Fail to capture the underlying complexity.

Generally $k < \sqrt{N}$. This helps maintain a good balance between capturing local structures in the data while avoiding oversmoothing. Balance between bias and variance.

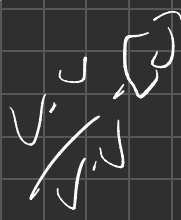
Evaluating Classifier:

- What's the accuracy?
- How badly did it get the wrong predictions.
- Which ones did it get wrong?

We can't use test sets for tuning meta-parameters as:
- Overfit (will be biased on test set it's tuned on)
- Biased Performance
- Test set should remain unseen.

Generalization Error: How well does the classifier do with data it's never seen?

Cross Validation: Choose best k by utilizing all test data rather than a single train-test split.



USE WHEN

Euclidean
+ Normally distributed/continuous
+ Emphasize larger differences (squares, weights larger differences)

Manhattan
- Contains outliers. that can skew results
- Working in high-dimensional space.

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Stats:

$$P(A|B) = \frac{P(A,B)}{P(B)}$$

$$P(+) = P(+,H) + P(+,DH)$$
$$= P(H) \times P(+|H) + P(DH) \times P(+|DH)$$

$$P(a,b) = P(b|a) \times P(a) = P(a|b) \times P(b)$$

$$P(a,b,c) = P(a|b,c) \times P(b,c) = P(a|b,c) \times P(b|c) \times P(c)$$

A and B are independent if $P(A,B) = P(A) \times P(B)$

A and B are conditionally independent given C if $P(A,B|C) = P(A|C) \times P(B|C)$

BAYES:

$$P(A|B) = \frac{P(B|A) \times P(A)}{P(B)} \quad //$$

EXPECTED VALUE: Average value given probabilities.

$$E[X] = \sum P(X=a) \times a$$

$$E[X+Y] = E[X] + E[Y]$$

$$E[cX] = cE[X]$$

VARIANCE: Measure the spread of a set around their mean. Shows average of how spread the data is compared to its mean.

$$Var(X) = E[(X-\mu)^2]$$

$$Var(cX) = c^2 var(X)$$

Ex For a dice

$E[X] = 3.5$

$Var(X) = \frac{1}{6} \times (1-3.5)^2 + \frac{1}{6} \cdot (2-3.5)^2 \ldots\ldots$

If X and Y are independent:

$$E[XY] = E[X]E[Y]$$

$$Var(X+Y) = Var(X) + Var(Y)$$

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Vectorization:

- Convert operations performed element by element into operations performed on entire arrays or vectors by taking advantage of modern CPU architectures that support parallel processing.

- Reduce overhead and processing time, increase performance.

```
array = np.array([1,2,3,4,5])

res = array + 5,,  # add 5 to each element.
```

np.sum(), np.mean()

Broadcasting = Perform operations on arrays of different shapes.

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Info THEORY:

$E[\text{Surprise}] = -\sum P(x) \cdot \log(P(x))$

$H(x) = 1 \rightarrow$ Maximum uncertainty
$H(x) = 0 \rightarrow$ Maximum certainty.

PROPERTIES:

$H(x,y) = H(x|y) + H(y) = H(y|x) + H(x)$

If x and y are independent.

$H(x|y) = H(x)$

$H(x|x) = 0$

$H(x|y) \leq H(x)$

$IG(x|y) = H(x) - H(x|y)$

if y doesnt help x at all:

$IG(x|y) = 0$

If y is completely informative about x

$IG(x|y) = H(y)$

Ex R, C = 0.24
R, NC = 0.01
NR, C = 0.25
NR, NC = 0.5

$IG(C|R) = H(C) - H(C|R)$

$0.49 \times \log(0.49) - 0.51 \times \log(0.51)$
$-\left(\frac{1}{4} \times H(\text{cloudy} | \text{is rain}) + \frac{3}{4} \times H(\text{cloudy} | NR\right)$

$IG(y|x) = H(y) - H(y|x)$

Decision Tree:	KNN
Fast	Slow
Interpretable	Harder to interpret.
Can handle missing data	Can't handle missing data.
Robust to scaling	Not robust to scaling.
Lot of hyperparams	Few hyperparams.

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LINEAR ALGEBRA:

$$U = \begin{bmatrix} 1 \\ 2 \end{bmatrix} \quad V = \begin{bmatrix} 3 \\ 4 \end{bmatrix} \quad A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \quad B = \begin{bmatrix} 7 & 8 \\ 9 & 10 \end{bmatrix}$$

$$A^T = \begin{bmatrix} 1 & 3 \\ 2 & 4 \end{bmatrix} \quad B^T = \begin{bmatrix} 7 & 9 \\ 8 & 10 \end{bmatrix}$$

$$U^T A = \begin{bmatrix} 1 & 2 \end{bmatrix} \cdot \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} = \begin{bmatrix} 1\times1+2\times3 & 1\times2+2\times4 \end{bmatrix} = \begin{bmatrix} 7, & 10 \end{bmatrix}$$

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