## Generative v.s. Discriminative Classifiers



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JUNE 2ND 2022

## Generative v.s. Discriminative Classifiers

- Training classifiers: $f: X \rightarrow Y$ or $P(Y \mid X)$
- Generative classifiers (e.g., Naïve Bayes)
- Assumption on $P(X \mid Y), P(Y)$
- Estimates parameters of $P(X \mid Y), P(Y)$ from training data
- Use Bayes rule to calculate $P(Y \mid X)$
- Discriminative classifers (e.g., Logistic Regression)
- Assumption on $P(Y \mid X)$
- Estimates parameters of $P(Y \mid X)$ directly from training data


## Which one to use

- Restrictiveness of modeling assumption
- NB assumes conditional independence
- Learning curve
- Rate of convergence (in amount of training data) toward asympototic (infinite data) hypothesis
- NB can converge faster if assumption is correct


## Gaussian Naïve Bayes v.s. Logistic Regression

- Assume Boolean $Y$, continuous $X_{i}, n$ features for $X$
- Number of parameters to estimate, or model size
- Gaussian Naïve Bayes

$$
P\left(X_{i} \mid Y=y_{k}\right) \sim \mathcal{N}\left(\mu_{i k}, \sigma_{i k}\right)
$$

- Gaussian Naïve Bayes, assume independent of $Y$

$$
P\left(X_{i} \mid Y=y_{k}\right) \sim \mathscr{N}\left(\mu_{i k}, \sigma_{i}\right)
$$

- Logistic Regression

$$
P(Y=1 \mid X, W)=\frac{1}{1+\exp \left(w_{0}+\sum_{i=1}^{n} w_{i} x_{i}\right)}
$$

## Gaussian Naïve Bayes v.s. Logistic Regression

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- Logistic Regression

$$
P(Y=1 \mid X, W)=\frac{1}{1+\exp \left(w_{0}+\sum_{i=1}^{n} w_{i} x_{i}\right)}, n+1
$$

## Asymptotic Comparison

Have infinite training samples

- When the conditional independence assumption is correct
- Identical classifiers
- When the assumption is incorrect
- Logistic Regression is less biased


## Convergence Rate

- Let $\epsilon_{\text {Algo, } m}$ refer to expected error of learning algorithm Algo after $m$ steps
- Let $n$ be the number of features for $X$

$$
\begin{aligned}
\epsilon_{L R, m} & =\epsilon_{L R, \infty}+O\left(\sqrt{\frac{n}{m}}\right) \\
\epsilon_{G N B, m} & =\epsilon_{G N B, \infty}+O\left(\sqrt{\frac{\log n}{m}}\right)
\end{aligned}
$$

