

# Bayesian approach to statistics



# Uncertainty interpretation

A frequentist would say: A coin flip has 1/2 heads probs, 1/2 tails probs.

Frequentist



A bayesian practitioner would say: We can parameterize the angle of the coin flip, velocity, thumb acceleration, etc. The outcome of the experiment can be predicted!

Bayesian



Subjective

Objective



# Data and parameters

Theta is parameters. X is the data.

The bayesian approach sorts of make sense.  
When we 're training a machine learning model for example,  
our data (X) is fixed, yet the parameters (theta) are random.

Frequentist



$\theta$  is random  
 $X$  is fixed

$\theta$  is fixed  
 $X$  is random

Bayesian



# Data and parameters

Frequentist



number of data doesn't matter.

For any  $|X|$

$$|X| \gg |\theta|$$

Datapoints must be significantly larger  
than number of parameters.

Bayesian



# Training

Find theta such that we get the highest probability of data given parameters theta.

Frequentist



Bayesian



Maximum Likelihood:

$$\hat{\theta} = \arg \max_{\theta} P(X|\theta)$$



# Training

Frequentist



We compute the posterior.

Bayes theorem:

$$P(\theta|X) = \frac{P(X|\theta)P(\theta)}{P(X)}$$

Bayesian



# Classification

For the bayesian method,

Training:

$$P(\theta|X_{\text{tr}}, y_{\text{tr}}) = \frac{P(y_{\text{tr}}|X_{\text{tr}}, \theta)P(\theta)}{P(y_{\text{tr}}|X_{\text{tr}})}$$

Prediction:

$$P(y_{\text{ts}}|X_{\text{ts}}, X_{\text{tr}}, y_{\text{tr}}) = \int P(y_{\text{ts}}|X_{\text{ts}}, \theta)P(\theta|X_{\text{tr}}, y_{\text{tr}})d\theta$$



# Regularization

Treat prior probability as a regularizer.

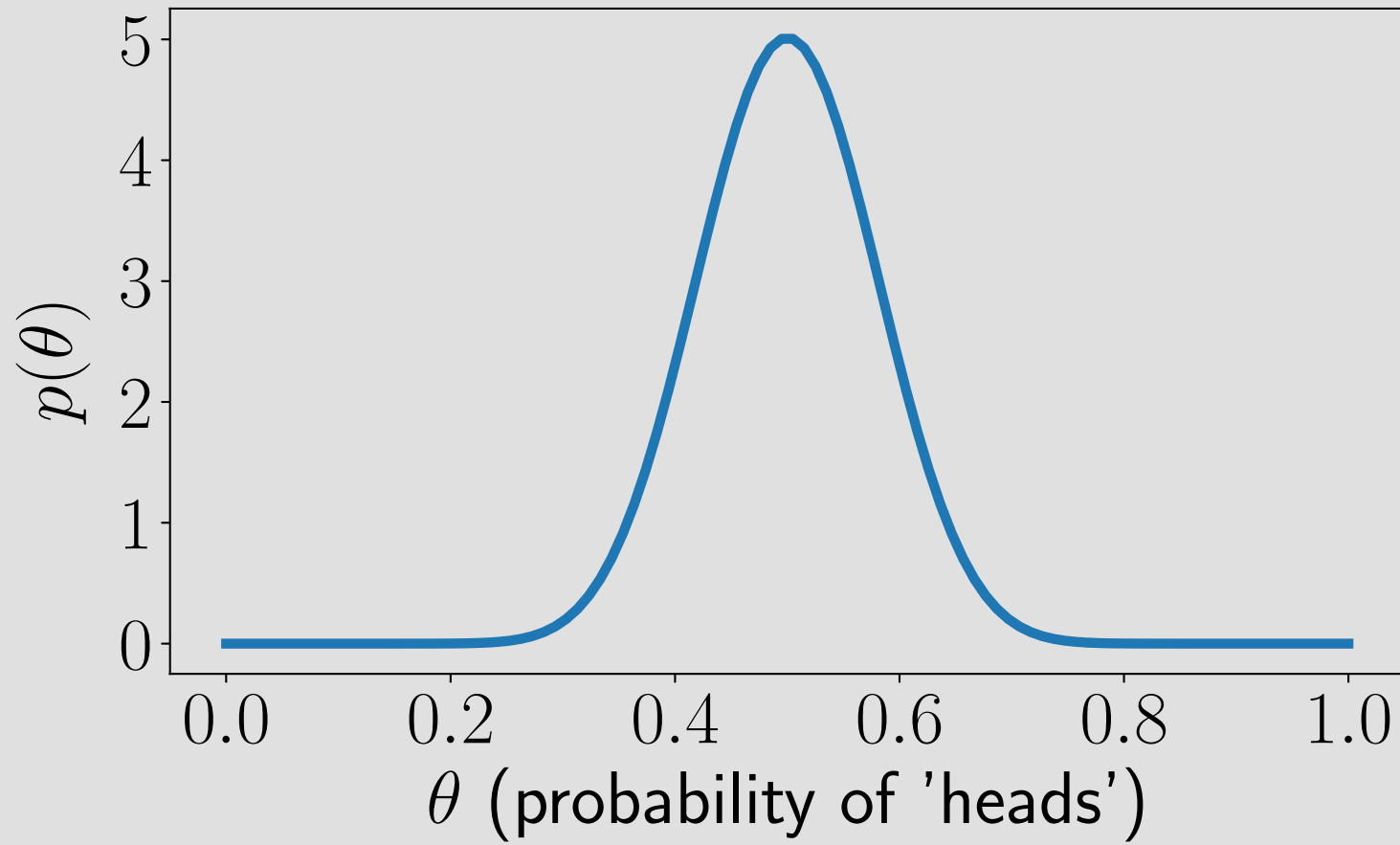
Regularizer

$$P(\theta|X) = \frac{P(X|\theta)P(\theta)}{P(X)}$$

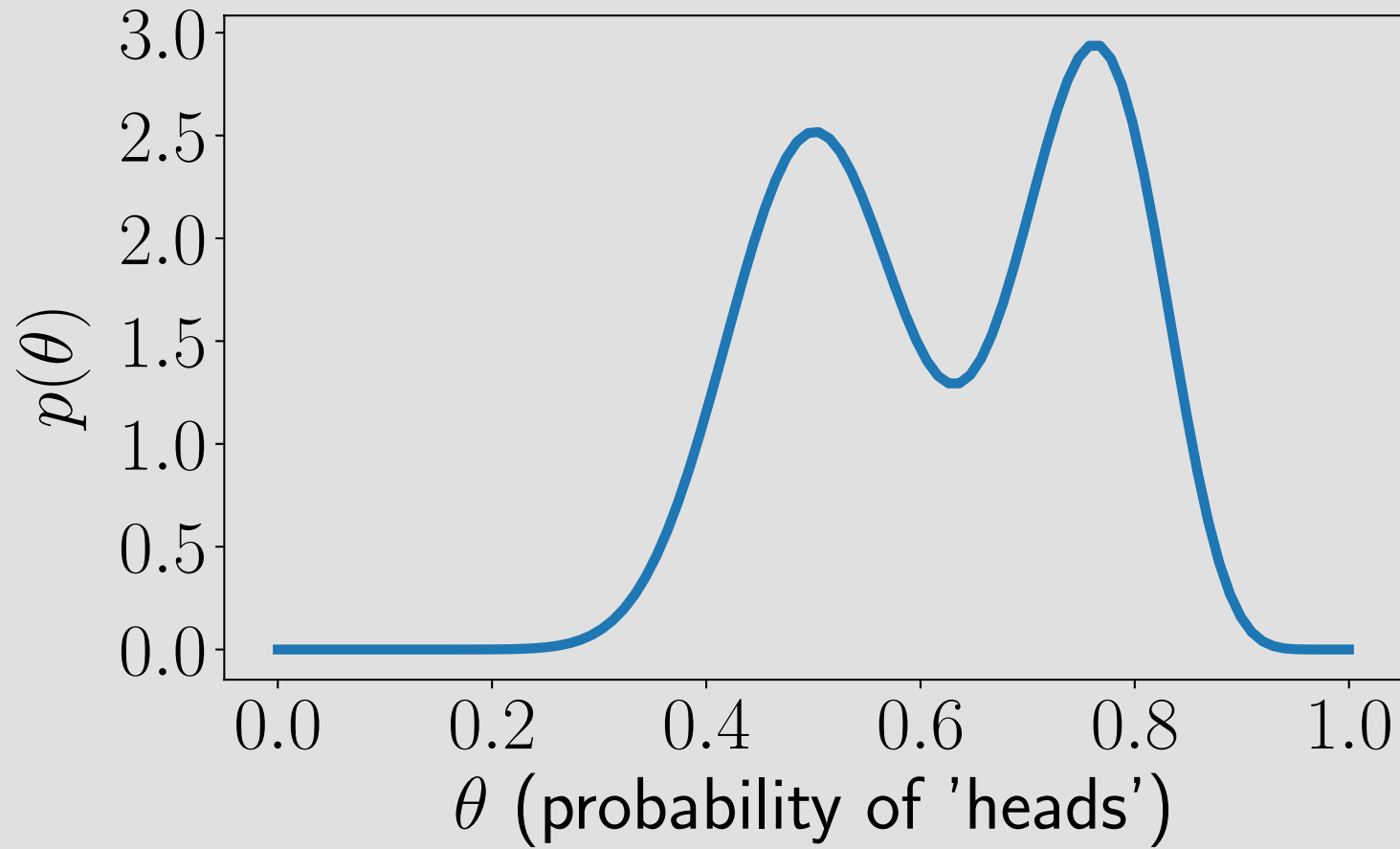




# Regularization



# Regularization



# On-line learning

New prior      Likelihood      Prior

$$P_k(\theta) = P(\theta|x_k) = \frac{P(x_k|\theta)P_{k-1}(\theta)}{P(x_k)}$$

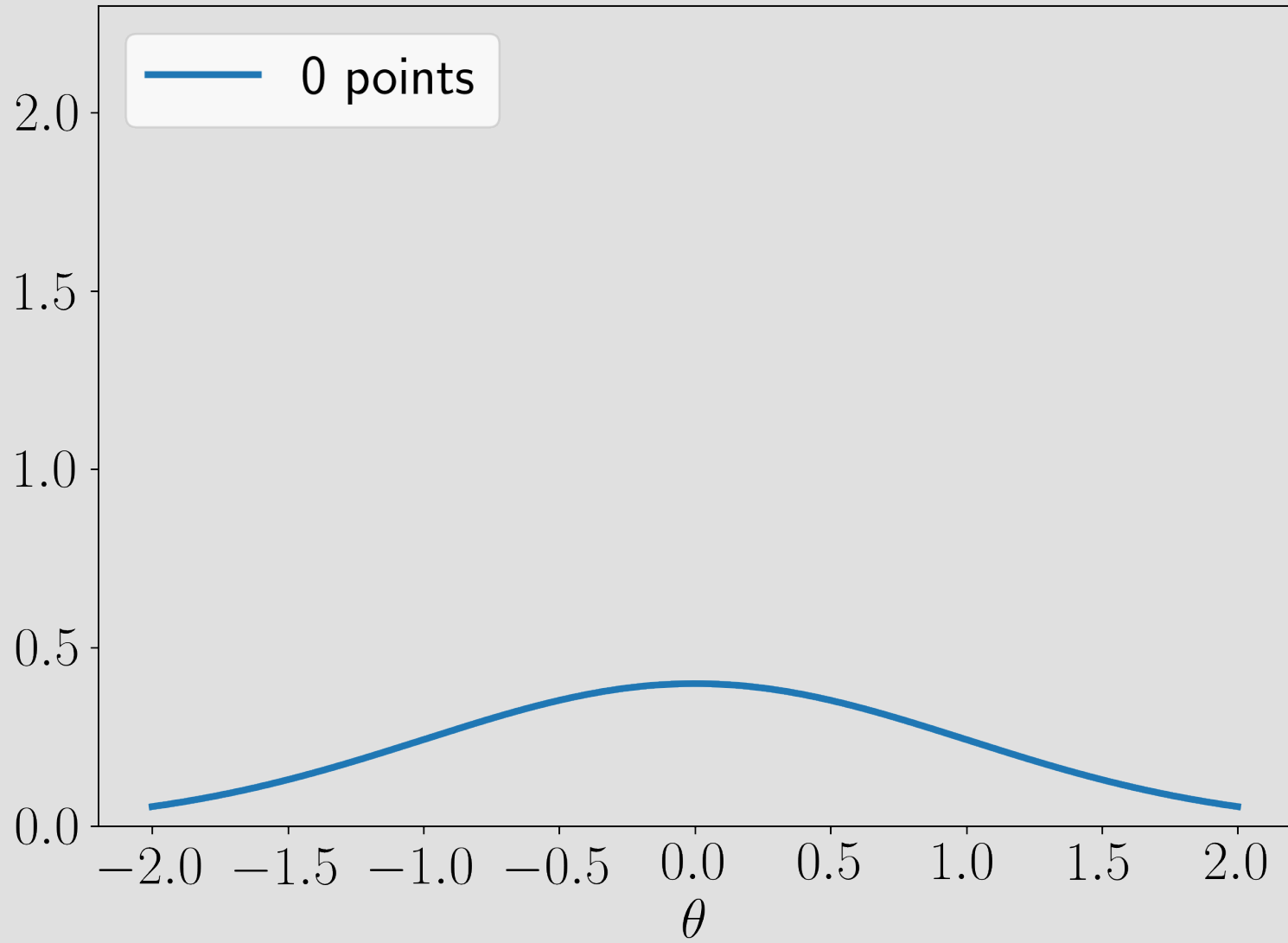
Posterior

Set prior to posterior.



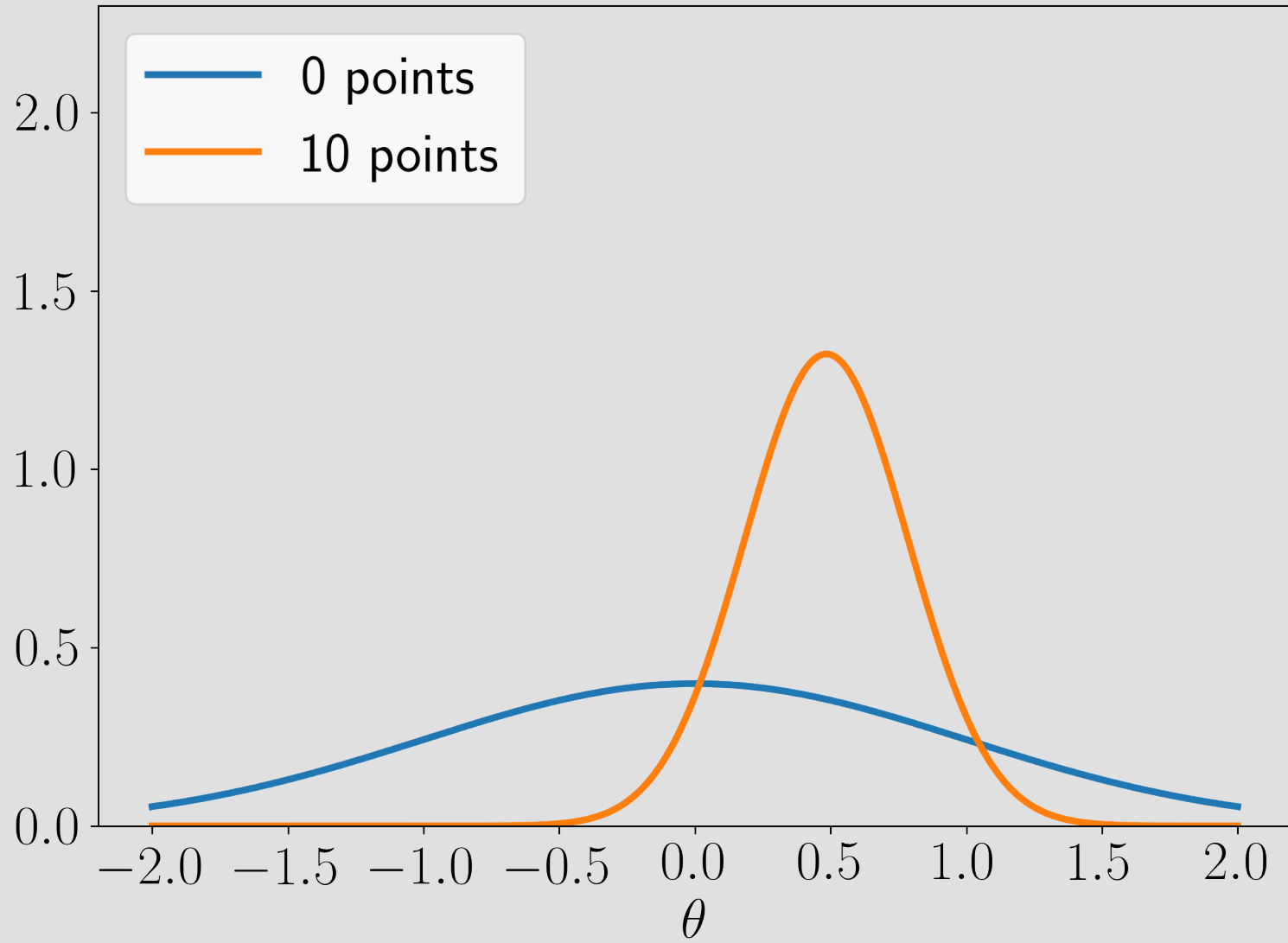
# On-line learning

Suppose we want to estimate the parameter  $\theta$ , and our prior is as follows:



# On-line learning

When we update our prior = posterior, we get a new shape. The variance of this distribution is less, and mean has changed.



# On-line learning

