ENM 360: Introduction to Data-driven Modeling

Lecture #9: Bayesian linear regression



Linear regression

$$f: \mathcal{X} o \mathcal{Y}$$
 $\mathcal{D} = \{oldsymbol{x}, oldsymbol{y} \in \mathcal{X}, oldsymbol{y} \in \mathcal{Y}$ $oldsymbol{y} = f(oldsymbol{x}) + \epsilon$ $f(oldsymbol{x}) = w^T oldsymbol{x}$

"It's not just about lines and planes!"

Linear regression with basis functions

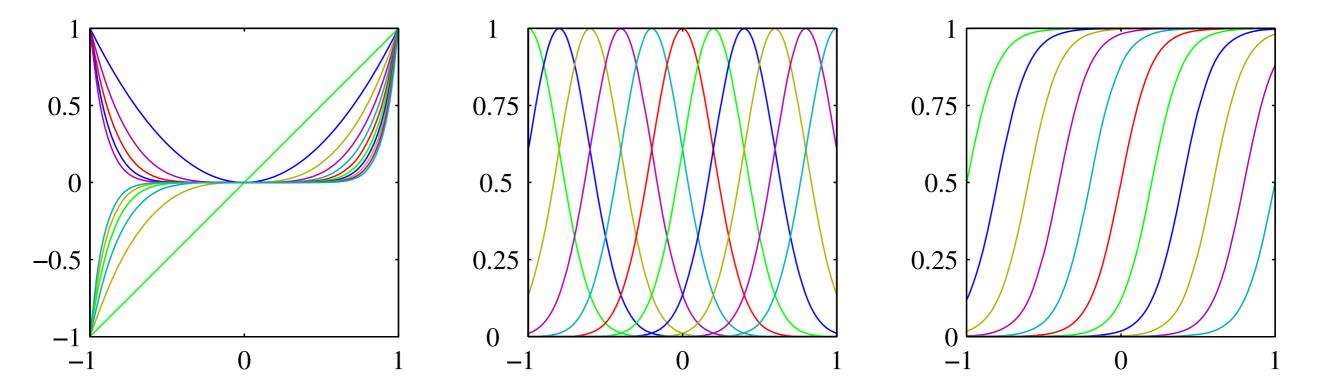
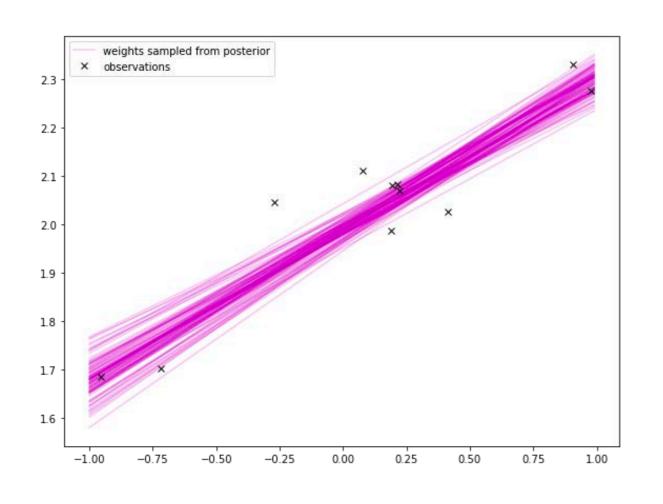
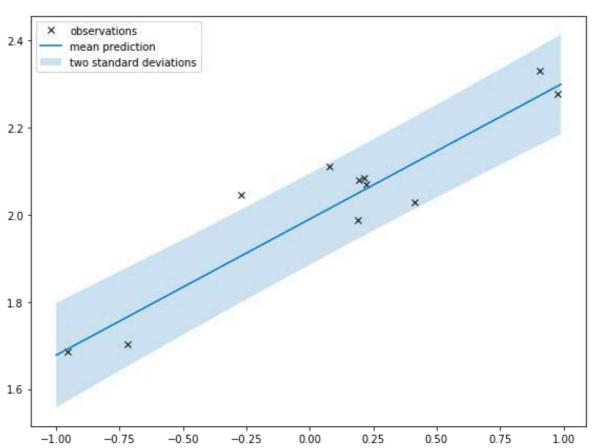
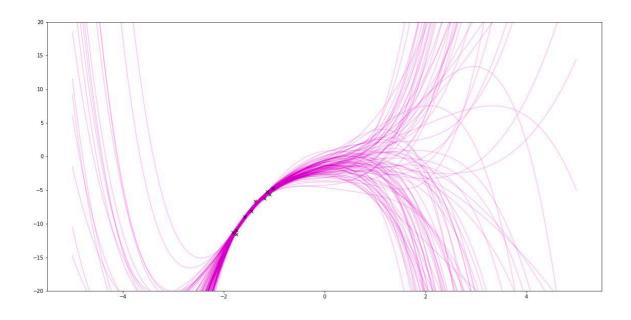


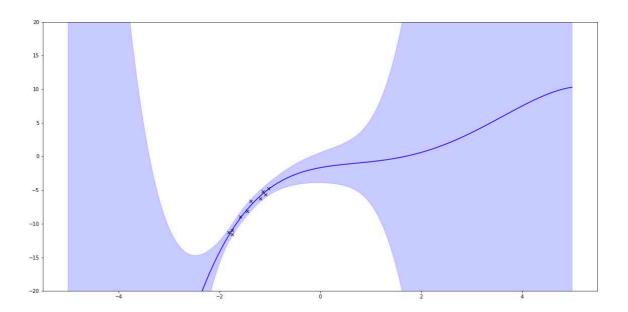
Figure 3.1 Examples of basis functions, showing polynomials on the left, Gaussians of the form (3.4) in the centre, and sigmoidal of the form (3.5) on the right.

Bayesian linear regression









Bayesian linear regression

```
12 class BayesianLinearRegression:
13
14
      15
      w \sim N(0, beta^{-1})I)
16
      P(y|x,w) \sim N(y|(w.T)*x,alpha^{(-1)}I)
17
18
    def __init__(self, X, y, alpha = 1.0, beta = 1.0):
19
20
        self.X = X
21
        self.y = y
22
        self.alpha = alpha
24
        self.beta = beta
25
26
        self.jitter = 1e-8
27
28
29
    def fit MLE(self):
30
        xTx_inv = np.linalg.inv(np.matmul(self.X.T,self.X) + self.jitter)
31
        xTy = np.matmul(self.X.T, self.y)
32
        w_MLE = np.matmul(xTx_inv, xTy)
33
34
        self.w MLE = w MLE
35
36
        return w_MLE
37
38
    def fit MAP(self):
39
        Lambda = np.matmul(self.X.T,self.X) + \
40
                 (self.beta/self.alpha)*np.eye(self.X.shape[1])
41
        Lambda_inv = np.linalg.inv(Lambda)
        xTy = np.matmul(self.X.T, self.y)
42
43
        mu = np.matmul(Lambda inv, xTy)
44
45
        self.w MAP = mu
46
        self.Lambda_inv = Lambda_inv
47
48
        return mu, Lambda_inv
49
50
    def predictive distribution(self, X star):
51
        mean_star = np.matmul(X_star, self.w_MAP)
52
        var_star = 1.0/self.alpha + \
53
                   np.matmul(X_star, np.matmul(self.Lambda_inv, X_star.T))
54
        return mean_star, var_star
```

