BOOSTING

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THE BASIC CHALLENGE

- Take a weak learner (one slightly better than random guessing)
- Turn it into a strong learner (one with arbitrary accuracy)

THE CONCEPTUAL IMPLEMENTATION

- Fit a learner to your data
- Evaluate the residuals
- Fit a learner to the residuals
- Grab the predictions from this model (which should correct the errors from the first model)
- Add the predictions to form your new predictions
- Repeat M times

THE CONCEPTUAL IMPLEMENTATION

\[F(x) = \sum_{i=1}^M F_i(x) \]

- Once we fit a learner, we keep its prediction
- We want to improve the prediction by seeing where it went wrong
- Predict the degree to which it went wrong
- Correct the original predictions

THE CONCEPTUAL MODEL

- \(h(x)\) is a weak learner
- Fit \(F_1(x)\) to your data
- \(F_2(x) = F_1(x) + h(x)\)
- \(F_3(x) = F_2(x) + h(x)\)
- and so on, for *M* iterations

LET’S SEE HOW THIS MIGHT WORK

GRADIENT DESCENT

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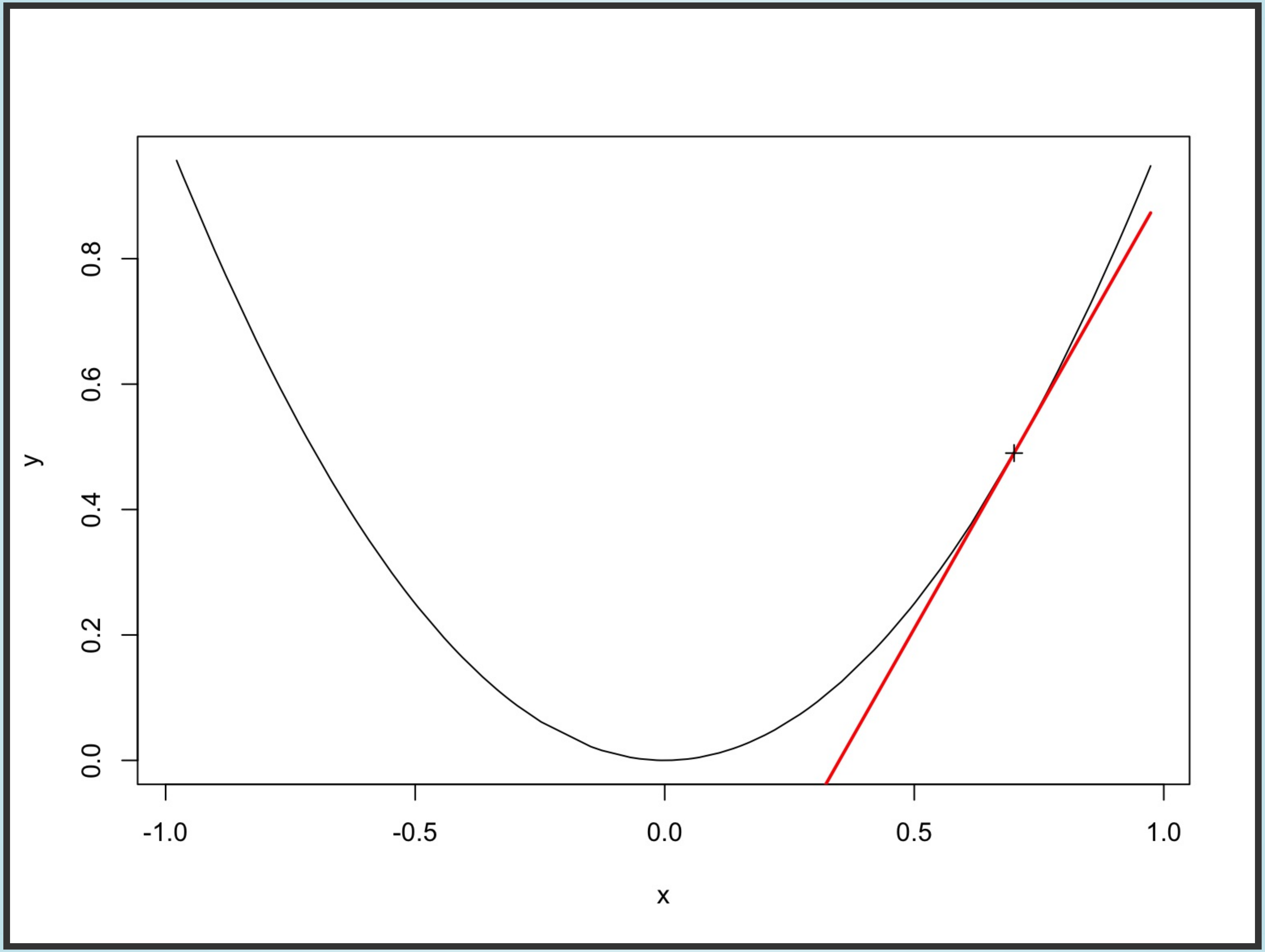
- Gradient descent is a way to minimize a function
- The idea is to follow a curve down its **steepest** path

GRADIENT DESCENT



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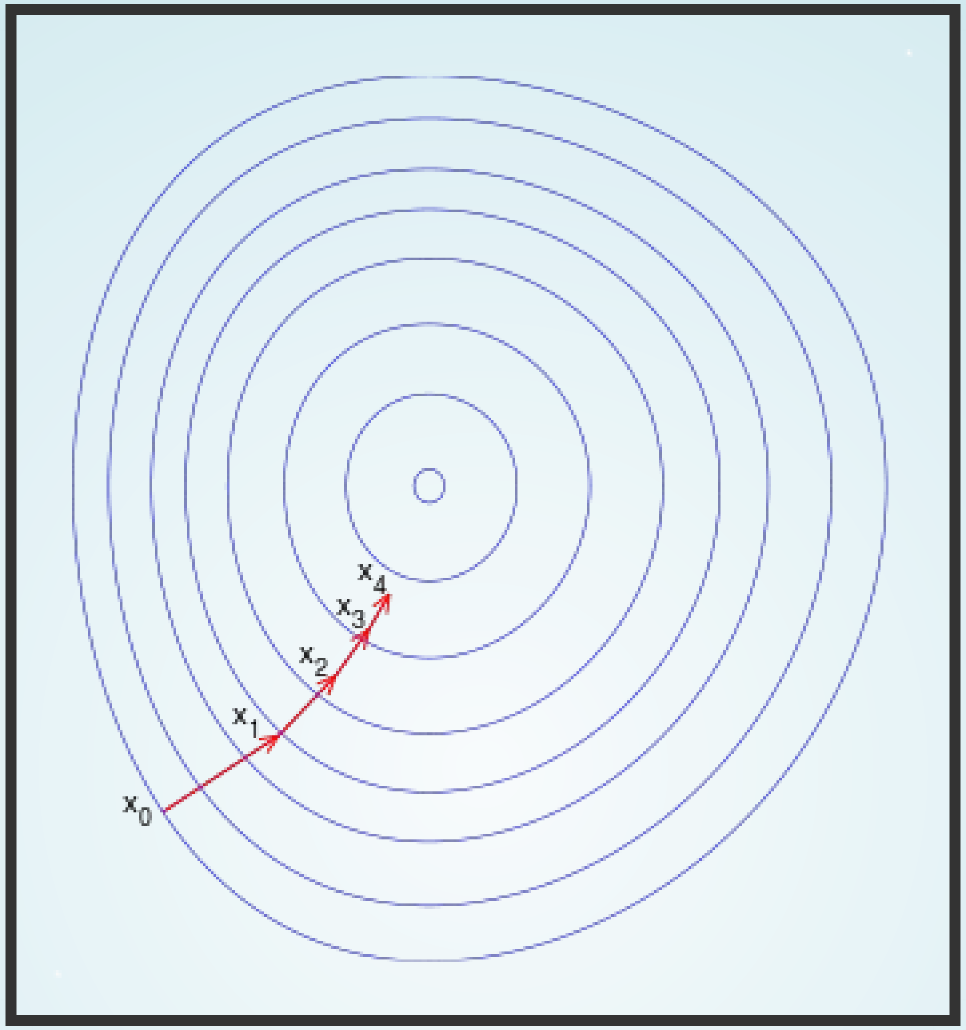

GRADIENT DESCENT

- Sometimes a “learning rate” \(\alpha\) is added, so you don’t move the whole way
- \(F_k(x) = F_{k-1}(x) + \alpha h(x)\)
- This is to slow things down
- If \(\alpha\) is small and \(M\) is large, then you will get to minimum. # Loss functions

GRADIENT DESCENT

- Conceptually think of residuals
- However, in reality, think in direction of gradient

LOSS FUNCTION MINIMIZATION

- We want to minimize a chosen loss function \(L(y, X)\)
- The gradient of this loss function is $
- This is a vector with length = number of columns of X
- Compute this at each point
- Move in that direction

SQUARED ERROR LOSS

- $L(y, x) = (y_i - x_i)^2/2$
- Gradient $G(x, y) = - (y_i - x_i)$
- Note that this is essentially the residual

LOGISTIC LOSS

- $L(y,x) = \log(1 + e^{-yx})$
- Gradient $G(x,y) = -ye^{-yx}/(1+e^{-yx})$
- This is often used for binary targets, where $y\in {0,1}$, and x is the predicted probabilities

STOCHASTIC GRADIENT DESCENT

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- We can overfit our data using just gradient descent
- Instead, fit learner to random subset of data, predict on remainder

STOCHASTIC GRADIENT DESCENT

- Also, at each stage, take a random sample of predictors
- Fit the model using this random sample of predictors

GRADIENT BOOSTED TREES

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- Weak learners are decision trees (in particular regression trees)
- Fit a regression tree to your data
- Compute residuals or gradients at each point
- Fit a regression tree to the residuals/gradients and predict
- Add the predictions to the previous predictions
- Repeat