EE147: Neural Networks and Deep Learning

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Winter 2021

Contents

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- deep learning has many modern applications:
  - Google search
  - Youtube video recommendations
  - Yelp restuarant best foods
  - Instagram feeds
  - very smart image recognition:
    * what makes a car a car?
    * cannot classify purely based on physical attributes such as size or number of wheels
    * image may be obscured or obfuscated
  - fraud detection
  - cancer treatment
  - self driving car:
    * many concerns eg. traffic cones, school buses, pedestrian signals, police cars
    * much expressive capacity is required
  - AlphaGo, Deepmind's AI that plays Go:
    * there are more Go board configurations than atoms in the unvierse
    * cannot do something as simple as a tree search
    * although AlphaGo was trained off of *"big data"* of Go experts:
      · its successor AlphaGo Zero uses deep reinforcement learning, *without* using any human data
      · algorithm rather than data based
  - brain-machine interfaces

History

- the concept of neural networks have been around for a long time, since McCulloch and Pitts in 1943:
  - but has only become relevant as of recently
  - this early model was inspired by the nervous system activity (and did not have the capacity to learn):
    1. all or none: a brain neuron either fires or not, ie. 1 or 0
    2. synpases can sum together to trigger a neuron
- in 1958, Rosenblatt propsed the first **NN (neural network)** that could learn:
  - called the **perceptron**, it had a learning rule to train it to perform clas-

sifications
  - had m neurons or inputs, , m weights, a bias b, and a value v
    * where $v = w_1 x_1 + ... + w_m x_m + b$
  - this early perceptron had a **hard-limiter** function φ st. the output $y = \varphi(v)$ and $\varphi(x)$ outputs 1 if $x > 0$ and otherwise 0
    * inspired by observation (1)
  - the perceptron could act as a linear classifier with one layer
    * but failed for nonlinear classifications, such as the XOR problem, with only one layer
  - thus, there was a lot of pessimism towards researching multilayer neural networks around this time

- researchers would continue to use biological inspiration for developing neural networks:
  - in 1962, Hubel and Wiesel published research on the cat V1 visual neural system
  - Fukushima's neocognitron from 1982 used the insights from these visual system in a new neural network architecture

- in 1986, Rumelhart used **backpropagation** to finally train multilayer neural networks:
  - a new way to train multilayer perceptrons by essentially using the chain rule to pass partial derivatives

- in 1989, LeCun and researchers at Bell Labs used neural networks to recognize handwritten zipcodes from the MNIST dataset

- in 1998, LeCun introduced LeNet, the modern **CNN (convolutional neural network)**, similarly inspired by visual cortex experiments:
  - took inspiration from spatial independence and simple linear composition of neurons in the V1 system
  - but still just a loose inspiration, eg. neurons in brains have probabilistic rather than static weights

- why didn't CNNs and backpropagation develop widespread use then?
  - backpropagation was still only good for shallow neural networks
    * as networks are deeper, the propagated derivative becomes more inaccurate
  - in addition, neural networks are data hungry

- modern era of deep learning:
  - the famous large ImageNet dataset with over 1000 classes of images held a yearly competition

    - within a decade, deep learning teams improved drastically in the ImageNet competition, from a 25% error rate to less than 5%
- driven by the massive amount of data we have access to and computation power to process it
    - GPU hardware have accelerated the training of NNs
- trend of more and more layers used in neural networks

Basics of Machine Learning

- **machine learning** uses statistical tools to estimate ie. *learn* functions, some of which may be fairly complex:
  - **classification** produces a discrete output representing the category given an input vector $x \in \mathbb{R}^n$:
    - ie. which of k categories x belongs to
    - eg. classifying whether an image is a cat or dog = class focuses on this type of function
  - **regression** produces an analog output predicting the value given an input
    - eg. predicting housing prices from square footage, controlling position and velocity of a cursor through brain signals
  - **synthesis and sampling** generate new examples that resemble a training data
    - eg. used in generative adversarial networks (GANs)
  - **data imputation** fills in missing values of a vector
    - eg. Netflix predicting if you will like a show or movie
  - **denoising** takes a corrupt data sample and outputs a cleaner sample
    - eg. used in variational autoencoders
  - other types
- in **supervised learning**, input vectors x and their target vectors y are known:
  - the goal is to learn function $y = f(x)$ that predicts y given x
  - eg. takes in a dataset D of n tuples of data
- in **unsupervised learning**, goal is to discover structure in input vectors, absent of knowledge of target vectors
  - eg. finding similar input vecotrs in clustering, distributions of the inputs, visualization, etc.
- in **reinforcement learning**, goal is to find suitable actions in certain scenarios to maximize a given reward R
  - discovers policies through trial and error
- in this class, we will focus on supervised learning:
  - using the CIFAR-10 dataset for an image classification problem:
    - 10 possible image categories
    - 32 by 32 pixel images, represented as 32 by 32 by 3 data values (RGB colors)
    - ie. input vector $x \in \mathbb{R}^{3072}$
  - want to find a function $f(x)$ that outputs one of the 10 categories

Supervised Learning Example

- for a problem of renting a home in Westwood, we want to know if we were getting a good deal:
  - given the square footage of a house, output how much monthly rent we should expect to reasonably pay based on the training data we have
- first, we should determine how we model data:
  1. determine inputs and outputs
     - input x is the square footage, and the output y is the rent
  2. what model should we use?
     - try a linear model $y = ax + b$
       - a, b are the **parameters** that must be found in this chosen model
     - a different model could have been chosen eg. a nonlinear, higher order polynomial
       - many more parameters to tune with
  3. how do we assess how good our model is?
     - we need a **loss function** that *scores* how good the model is
     - for a prediction $\hat{y}_i = f(x_i)$ and actual sample output y_i, we can use a least squares loss function:

$$\textit{loss} = \textit{cost} = \sum_i (y_i - \hat{y}_i)^2$$

       - note that using least squares rather than absolute value puts higher weight on outlilers
- transforming with vectors:
  - writing the model using vectors where $\theta = \begin{bmatrix} a \\ b \end{bmatrix}$ and $\hat{x} = \begin{bmatrix} x \\ 1 \end{bmatrix}$:

$$\begin{aligned} \hat{y} &= ax + b \\ &= \theta^T \hat{x} \end{aligned}$$

  - writing the cost function using vectors where k is a normalization constant:

$$\begin{aligned} L(\theta) &= k \sum_i (y_i - \hat{y}_i)^2 \\ &= k \sum_i (y_i - \theta^T \hat{x}_i)^2 \end{aligned}$$

- we want to make loss $L(\theta)$ as *small* as possible, since θ represents the parameters we can control:
  - in this case, $L(\theta)$ will look like a parabola since it is squared
    - can solve for its minimum using optimization

1. calculate $\frac{dL}{d\theta}$
   - tells us the slope of the line with respect to θ
2. solve for θ such that $\frac{\partial L}{\partial \theta} = 0$

- however, θ is a vector, so how do we take derivatives with respect to it?
  - these derivatives are typically called **gradients** eg. $\frac{\partial y}{\partial x}$ or $\nabla_x y$
  - can be done with respect to vectors or matrices
  - see entry in appendix

- rewriting the cost function:

$$
\begin{aligned}
L &= \frac{1}{2}\sum_{i=1}^{N}(y_i - \theta^T \hat{x}_i)^2 \\
&= \frac{1}{2}\sum_{i=1}^{N}(y_i - \theta^T \hat{x}_i)^T(y_i - \theta^T \hat{x}_i) \\
&= \frac{1}{2}\sum_{i=1}^{N}(y_i - \hat{x}_i^T \theta)^T(y_i - \hat{x}_i^T \theta) \\
&= \frac{1}{2}(\begin{bmatrix} y_1 \\ \vdots \\ y_N \end{bmatrix} - \begin{bmatrix} \hat{x}_1^T \\ \vdots \\ \hat{x}_N^T \end{bmatrix} \theta)^T(\begin{bmatrix} y_1 \\ \vdots \\ y_N \end{bmatrix} - \begin{bmatrix} \hat{x}_1^T \\ \vdots \\ \hat{x}_N^T \end{bmatrix} \theta) \\
&= \frac{1}{2}(Y - X\theta)^T(Y - X\theta) \\
&= \frac{1}{2}(Y^T - \theta^T X^T)(Y - X\theta) \\
&= \frac{1}{2}[Y^T Y - Y^T X\theta - \theta^T X^T Y + \theta^T X^T X\theta] \\
&= \frac{1}{2}[Y^T Y - 2Y^T X\theta + \theta^T X^T X\theta]
\end{aligned}
$$

  - where $Y \in \mathbb{R}^{N\times 1}$ and $X \in \mathbb{R}^{N\times 2}$
    - note that $\theta^T \hat{x}_i = \hat{x}_i^T \theta$ and $Y^T X\theta = \theta^T X^T Y$ since they are all scalars and inner product is commutative
  - we used **vectorization** to move from summation to a sum expressed as an equivalent inner product of vectors

- now we can take derivatives to optimize the cost function:

$$
\begin{aligned}
\frac{\partial L}{\partial \theta} &= \frac{1}{2}[0 - 2X^T Y + [X^T X + X^T X]\ \theta] \\
&= -X^T Y + X^T X\theta\ [=]\ 0 \\
X^T Y &= X^T X\theta \\
\theta &= (X^T X)^{-1} X^T Y \\
&\triangleq X^{\dagger} Y
\end{aligned}
$$

  - recall that $\frac{\partial z^T \theta}{\partial \theta} = z$ and $\frac{\partial \theta^T A\theta}{\partial \theta} = (A + A^T)\theta$

    - $Y^T X$ can be considered as a vector z
  - this solution $\theta = X^\dagger Y$ is called the **least-squares solution**
    - gives us the best parameters θ to minimize the least-squares cost
- does our current least-squares formula allow for learning nonlinear polynomial fits of the form:

$$y = b + a_1 x_1 + a_2 x^2 + \cdots + a_n x^n$$

  - yes, we just have to redefine the input vectors:

$$\hat{x} = \begin{bmatrix} 1 \\ x \\ x^2 \\ \vdots \\ x^n \end{bmatrix}, \quad \theta = \begin{bmatrix} b \\ a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix}$$

  - a higher degree polynomial will *always* fit the training data *no worse* than a lower degree polynomial
    - encapsulates lower degree polynomials and can implement them by just setting the necessary coefficients to 0
  - but do we always want the highest possible degree polynomial?
    - eg. for housing price example, the linear model performs best for new inputs
    - the fundamental problem is that more complex models may not *generalize* as well if the data came from a different model
      - ie. relying on fitting the training data instead of generalizing

Maximimum Likelihood Optimization

- note that there are alternative types of optimization rather than minimizing a mean-square error:
  - may want to instead *maximize* the probability of having *observed* the data
- ex. given a weighted coin and a sequence of flips, want to find the coins weight θ:
  - consider the example training data of `HTHHTTHT`
  1. if $\theta = 1$, the probability of observing the data is 0
  2. if $\theta = 0.75$, the probability of observing the data is $0.75^4 0.25^4 = 0.00124$
  3. if $\theta = 0.5$, the probability of observing the data is $0.5^4 0.5^4 = 0.0039$
  - thus we would want to choose model (3) since it maximizes the likelihood of seeing the data
- ex. given paired data $\{x_i, y_i\}$ where the coordinate $x_i \in \mathbb{R}^2$ belongs to one of three classes y_i, want to be able to estimate the class of a new coordinate

Generalizing the Model

- dangers of overfitting / underfitting:
  - **training data** is data that is used to learn the parameters of the model
  - **validation data** is the data used to optimize the hyperparameters of the model:
    - **hyperparameters** are the design choices of the model, eg. the order of the fitted polynomial
    - avoids the potential of overfitting to nuances in the testing dataset
  - **testing data** is data that is excluded in training and used to score the model
    - a "pristine" dataset used to score the final model with set parameters and hyperparameters
  - all datasets should follow the same distributions
  - a model with very low training error but high testing error is called **overfit**:
    - beyond a certain point, model begins to overfit the data
  - addressing overfitting:
    - more data helps ameliorate the issue of overitting
      - may be appropriate to use more complex models when given much more data
    - regularization is another useful technique
- picking a best model:
  1. assess its generalization ie. validation error
  2. pick a setting of the parameters that results in minimal value
  - there are some scenarios where the database size is so limited that it is better to utilize model selection techniques
    - ie. penalizes the model for being overly complex
- evaluating generalization error:
  - in a common scenario, we are given a training and testing dataset
  - to train a model while validating hyperparameters, one common approach is k-fold **cross validation**:
    - split training data into k equal sets called **folds**, each with $\frac{N}{k}$ examples
    - $k-1$ folds are training datasets, while the remaining fold is a validation dataset
    - for each hyperparameter eg. polynomial order we are trying to validate
      - run k validation tests using each of the folds as a validation set, take the average as an overall validation error
    - note that class balance should be maintained across folds eg. using a stratified k-fold

- after using cross validation to finalize hyperparameters, we can train a single model based on the entire training data

Appendix

Python Libraries

NumPy

- `random.uniform(low, high, size)` draws `size` samples from a uniform distribution between `low` and `high`
- `random.normal(loc, scale, size)` draws `size` samples from a normal distribution with mean `loc` and standard deviation `scale`

MatPlotLib

- `plt.figure` creates a new figure
- `Figure.gca` gets the current axes of a figure
- `Axes.plot(x, y, fmt)` plots a figure with points or line nodes given by x, y
  - `fmt` is a format string eg. `'ro'` for red circles, `'.'` for dots, `'x'` for crosses
- `Axes.set_xlabel(lbl)` and `Axes.set_ylabel(lbl)` sets the labels for the axes

Linear Algebra Review

Vectors

- $x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$ is a **column vector** with n elements
- $z = [z_1 z_2 \dots z_n]$ is a **row vector** with n elements
- the **transpose** of a column vector is a row vector, and vice versa
  - eg. $x = [x_1 x_2 \dots x_n]^T$

- the **dot product** of two column vectors is given by:

$$x^T y = \sum_{i=1}^{n} x_i y_i$$

  - the dot product of two vectors is commutative
- the **norm** of a vector measures its length
- the **p-norm** of a vector is given by the following, where $p \geq 1$:

$$||x||_p = (\sum_{i=1}^{n} |x_i|^p)^{\frac{1}{p}}$$

- the **Euclidian norm** is the 2-norm, and can also be writen as:

$$||x|| = ||x||_2 = \sqrt{x^T x}$$

  - the 2-norm is often more convenient to work with
  - a **unit vector** is a vector with $||x||_2 = 1$
- the dot product can also be written as the following, where θ is the angle between the vectors:

$$x^T y = ||x||||y||cos\theta$$

- x and y are **orthogonal** if $x^T y = 0$:
  - if both vectors have nonzero norm, than they are at a 90 degree angle to each other
  - in $\mathbb{R}^n$ at most n vectors may be mutually orthogonal with nonzero norm
  - if the vectors are orthogonal and also have unit norm, they are **orthonormal**
- a **linear combination** of vectors is a summation of those vectors scaled by a constant:

$$\sum_i c_i v_i$$

  - the **span** of a set of vectors is the set of all points obtainable by linear combinations of the vectors

Matrices

- $A = \begin{bmatrix} a_{11} \dots a_{1n} \\ \vdots \quad \ddots \quad \vdots \\ a_{m1} \dots a_{mn} \end{bmatrix}$ is an $m \times n$ **matrix**

- the product operation of two matrices $C = AB$ is defined by:

$$C_{ij} = \sum_k A_{ik} B_{kj}$$

  - matrix multiplication is distributive and associative
  - however, it is *not* commutative

- matrix multiplication is usually used to write down a system of linear equations, where $A \in \mathbb{R}^{m \times n}, b \in \mathbb{R}^m, x \in \mathbb{R}^n$:

$$Ax = b$$

$$\begin{aligned} A_1 x &= b_1 \\ A_2 x &= b_2 \\ &\dots \\ A_m x &= b_m \end{aligned}$$

  - this system can be solved using **matrix inversion** where $A^{-1}A = I_n$ and I_n is the $n \times n$ **identity matrix**:

$$\begin{aligned} Ax &= b \\ A^{-1}Ax &= A^{-1}b \\ I_n x &= A^{-1}b \\ x &= A^{-1}b \end{aligned}$$

  - however, $Ax = b$ may not always have a solution:
    - the **column space** is the span of the columns of A
    - to have a solution for all values of $b \in \mathbb{R}^m$, the column space of A must be all of $\mathbb{R}^m$
    - thus A should have at least m columns or $m > n$:
      - however, some of the columns may be redundant ie. **linearly dependent** as well
      - in addition, we need each equation to have at *most* one solution for each value of b, so A can also have at most m columns
    - therefore, the system will have a solution if it is square and all the columns are **linearly independent** ie. no vector in the columns is a linear combination of the other vectors
      - a square matrix with linearly dependent columns is **singular**
    - the **rank** of a matrix is the number of linearly independent columns it has

- the **determinant** of a square matrix $det(A)$ is a function that maps matrices to real scalars:

  - the determinant is equal to the product of all eigenvalues of a matrix
  - thus, since eigenvalues measure the scaling of eigenvectors, the absolute value of the determinant is a measure of how much the matrix expands or contracts space
  - if the determinant is 0, then space is contracted *completely* along at least one dimension, losing all its volume

- the **transpose** of a matrix satisfies:

$$A_{ij} = (A^T)_{ji}$$

  - a matrix is **symmetric** if $A = A^T$

- if the matrix is square ie. $m = n$ with rank n, then the **inverse** of a matrix satisfies the following, where I is the $n \times n$ **identity** matrix:

$$A^{-1}A = AA^{-1} = I$$

- the **trace** of a matrix is the sum of its diagonal elements:

$$tr(A) = \sum_{i=1}^{n} a_{ii}$$

  - the trace operator is invariant to transposition:

$$tr(A) = tr(A^T)$$

  - the trace operator is invariant to cyclic permutations of its input (even if the resulting product has different shapes):

$$tr(ABC) = tr(CAB) = tr(BCA)$$

  - the trace operator is linear:

$$tr(aX + bY) = atr(X) + btr(Y)$$

- the **Frobenius norm** of matrix $A \in \mathbb{R}^{m \times n}$ is:

$$||A||_F = \sqrt{\sum_{i=1}^{m}\sum_{j=1}^{n} |a_{ij}|^2} = \sqrt{tr(AA^T)}$$

- a **diagonal** matrix consists of only nonzero entries along the main diagonal:
  - ie. $D_{ij} = 0 \ \ \forall \ \ i \neq j$
  - eg. the identity matrix
  - useful properties of diagonal matrices:

    - multiplying by a diagonal matrix is computationally efficient
        - to find Dx, we just need to scale each element x_i by D_{ii}
    - to compute the inverse of a square diagonal matrix where each element on the diagonal is nonzero, just take the reciprocal $\frac{1}{D_{ii}}$ on the diagonal
    - nonsquare diagonal matrices do not have inverses, but can still be multiplied cheaply

- a **symmetric** matrix is one that is equal to its own transpose $A = A^T$
- given a symmetric matrix A:
    - A is called **positive definite** if $x^T Ax > 0 \ \forall \ x$
    - if $x^T Ax \geq 0$, A is **positive semidefinite**
    - similarly for **negative definite** and **negative semidefinite** matrices
- an **orthogonal matrix** is a square matrix whose rows are mutually orthonormal and whose columns are mutually orthonormal:

$$A^T A = AA^T = I$$

$$A^-1 = A^T$$

    - thus the inverse of these matrices are easily computed

Decomposition

- an **eigenvector** u_i and its corresponding **eigenvalue** λ_i of a square matrix $A \in \mathbb{R}^{n \times n}$ satisfy:

$$Au_i = \lambda_i u_i$$

    - the eigenvalues can be found by solving:

$$det(A - \lambda I) = 0$$

- collecting all of A's eigenvectors and eigenvalues into the following matrices gives the following **eigendecomposition** of A:

$$U = [u_1 u_2 ... u_n] \quad \Lambda = \begin{bmatrix} \lambda_1 & 0 & ... & 0 \\ 0 & \lambda_2 & ... & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & ... & \lambda_n \end{bmatrix}$$

$$A = U\Lambda U^{-1}$$

    - this decomposes square matrices in a *unique*, guaranteed way that show us information about their fundamental functional properties

  - tells us that these transformations *scale* space by eigenvalue λ_i in the direction of eigenvector v_i
  - in addition, makes the calculation of A^p easier, since $A^p = U\Lambda^p U^{-1}$

- specifically, if U's columns are an orthonormal set of the eigenvectors:

$$A = U\Lambda U^T$$

- the eigendecomposition can be derived as follows from the definition of an eigenvector:

$$\begin{aligned} Au_1 &= \lambda_2 u_1 \\ Au_2 &= \lambda_2 u_2 \\ A\begin{bmatrix} u_1 u_2 \end{bmatrix} &= \begin{bmatrix} u_1 u_2 \end{bmatrix} \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} \\ AU &= U\Lambda \\ A &= U\Lambda U^{-1} \end{aligned}$$

- if A is **normal**, then its eigenvectors are **orthonormal**:

$$u_i^T u_j = 0 \ \ \forall \ \ i \neq j, \quad u_i^T u_i = 1$$

- the **singular value decomposition (SVD)** of a matrix $A \in \mathbb{R}^{m \times n}$ is:

$$A = U\Sigma V^T$$

  - where U is an $m \times m$ matrix with orthonormal columns and V is an $n \times n$ matrix with orthonormal columns
    * the columns of U are the **left singular vectors** of A and are the orthonormal eigenvectors of AA^T
    * the columns of V are the **right singular vectors** of A and are the orthonormal eigenvectors of $A^T A$
  - Σ is a diagonal $m \times n$ matrix with σ_i as its ith diagonal element
    * σ_i is called the ith **singular value** of A and can be calculated as:

$$\sigma_i = \lambda_i^{\frac{1}{2}}(A^T A) = \lambda_i^{\frac{1}{2}}(AA^T)$$

  - essentially factorizing a matrix into singular vectors and singular values by performing an eigendecomposition for $A^T A$
  - unlike an eigendecomposition, SVD is applicable to nonsquare matrices as well eg. can solve $Ax = b$ for nonsquare and perform **principal component analysis (PCA)**

Mathematical Tools

- useful properties of common functions:
  1. the **logistic sigmoid**:
  $$\sigma(x) = \frac{1}{1 + e^{-x}}$$
     - commonly used to produce the probability parameter of a Bernoulli distribution
     - its range is $(0, 1)$, and saturates when its argument is very positive or negative
  2. the **softplus function**:
  $$\zeta(x) = log(1 + e^{x})$$
     - useful for producing the $\sigma = \frac{1}{\beta}$ parameter of a normal distribution
     - its range is $(0, \infty)$

Probability

- notation note:
  - $Pr(E)$ is the probability of the event E
  - $Pr(X = x)$ or equivalent shorthand $p(x)$ is the probability of random variable X taking on the value x
- manipulating probabilities revolves around two main rules:
  1. the **law of total probability** ie. sum rule:
  $$p(x) = \sum_{y} p(x, y), \quad x, y \text{ discrete}$$
  $$p(x) = \int_{y} p(x, y)dy, \quad x, y \text{ continuous}$$
     - more particularly, if $A_1, \dots, A_n$ forms a partition of the sample space S, then the probability of an event B is:
     $$Pr(B) = \sum_{i=1}^{n} Pr(B \cap A_i)$$
     - alternatively, using the conditional probability definition:
     $$Pr(B) = \sum_{i=1}^{n} Pr(B|A_i)Pr(A_i)$$

2. the **probability chain rule** ie. product rule:

$$\begin{aligned} Pr(E_1, E_2) &= Pr(E_1)Pr(E_2|E_1) \\ &= Pr(E_2)Pr(E_1|E_2) \end{aligned}$$

   - used to break up a joint probability into a product probability
   - can be further decomposed as follows:

$$\begin{aligned} p(w, x, y, z) &= p(w, x)p(y, z|w, x) \\ &= p(x)p(w|x)p(y, z|w, x) \\ &= p(x)p(w|x)p(z|w, x)p(y|z, w, x) \end{aligned}$$

     * any event that has been in front of the conditioning bar must be bind the conditioning bar for all other probability expressions
     * ie. assuming a random variable *has* taken on a value, and evaluating the remaining events
   - can also represent conditional independencies in graphical models
   - generalized for a joint probability over many variables:

$$p(x_1, \dots, x_n) = p(x_1) \prod_{i=2}^{n} p(x_i|x_1, \dots, x_{i-1})$$

     * could be proved through induction

- **Bayes' rule** gives the following relationship:

$$p(x|y) = \frac{p(y|x)p(x)}{\sum_x p(y|x)p(x)}$$

- an intuition on **Bayesian inference**, which appears frequently in machine learning:
   - let x represent model parameters we wish to infer denoted θ and y correspond to data we have observed D:

$$p(\theta|D) = \frac{p(D|\theta)p(\theta)}{\sum_x p(D|\theta)p(\theta)}$$

   - $p(\theta|D)$ is the **posterior distribution**, ie. the probability distribution of model parameters given the data
   - $p(D|\theta)$ is the **likelihood** of the data, ie. the probability of having seen the data given a chosen set of model parameters
   - $p(\theta)$ are **prior parameters**, ie. the probabilities of the model parameters *absent* of any data

    - we can consider that the prior is *updated* by the likelihood to arrie at the posterior distribution on the parameters
  - in Bayesian inference, we calculate $p(\theta|D)$, giving a distribution over the model parameters given the data we observed
    - concretely gives us all the parameters of our model
  - in **Frequentist inference** or **maximum-likelihood estimation**, we calculate $p(D|\theta)$, wanting to infering the θ that makes the data most likely to have been observed
    - ie. we choose the parameters that maximize the likelihood of the data

Derivatives

- in machine learning, we want to find the *best* model according to some performance metric:
  - this requires **optimization**, in which derivatives are crucial
  - in simple cases, we can find minima and maxima by simply setting the derivative equal to 0
  - however, in more complex cases, there is no closed-form solution, but the derivative is still useful in telling us how a change in the model parameters will affect the performance
- the definition of a **derivative** of a function $f : \mathbb{R} \to \mathbb{R}$ at a point $x \in \mathbb{R}$ is:

$$f'(x) = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$

  - gives how much a small change in x affects f:

$$f(x + \varepsilon) \approx f(x) + \varepsilon f'(x)$$

  - given $y = f(x)$, we denote the derivative of y with respect to x as $\frac{dy}{dx}$, such that:

$$\Delta y \approx \frac{dy}{dx} \Delta x$$

- the **scalar chain rule** states that if $y = f(x)$ and $z = g(y)$:

$$\frac{dz}{dx} = \frac{dz}{dy}\frac{dy}{dx}$$

  - ie. a small change in x will cause a small change in y that will in turn cause a small change in z as follows:

$$\begin{aligned} \Delta y &\approx \frac{dy}{dx} \Delta x \\ \Delta z &\approx \frac{dz}{dy} \Delta y \\ &= \frac{dz}{dy}\frac{dy}{dx} \Delta x \end{aligned}$$

- the **gradient** generalizes the scalar derivative to multiple dimensions:
  - if $f : \mathbb{R}^n \to \mathbb{R}$ transforms a vector toa scalar and $y = f(x)$, the gradient is:

$$\nabla_x y = \begin{bmatrix} \frac{\partial y}{\partial x_1} \\ \frac{\partial y}{\partial x_2} \\ \vdots \\ \frac{\partial y}{\partial x_n} \end{bmatrix}$$

  - the gradient is a vector that is the same size as x
  - each dimension of $\nabla_x y$ tells us how small changes in x in that dimension affect y
  - ie. after changing the ith dimension of x by a small amount affects y as follows:

$$\Delta y \approx \frac{\partial y}{\partial x_i} \Delta x_i$$

    - equivalently, $\frac{\partial y}{\partial x_i} = (\nabla_x y)_i$
  - similarly, after changing multiple dimensions of x, y is changed as follows in a dot product:

$$\begin{aligned} \Delta y &= \sum_i \frac{\partial y}{\partial x_i} \Delta x_i \\ &= (\nabla_x y)^T \Delta x \end{aligned}$$

- ex. if $f(x) = \theta^T x$, find $\nabla_x f(x)$ where $\theta, x \in \mathbb{R}^n, y \in \mathbb{R}$:
  - by rules of the gradient, $\nabla_x y \in \mathbb{R}^n$
  1. expand the dot product in $f(x)$:

$$f(x) = \theta_1 x_1 + ... + \theta_n x_n$$

  2. write out the gradient:

$$\nabla_x y = \begin{bmatrix} \theta_1 \\ \vdots \\ \theta_n \end{bmatrix} = \theta$$

  - dimensions match up
- ex. if $f(x) = x^T A x$, find $\nabla_x f(x)$ where $A \in \mathbb{R}^{n \times n}, x \in \mathbb{R}^n, y \in \mathbb{R}$:
  - by rules of the gradient, $\nabla_x y \in \mathbb{R}^n$
  1. expand $f(x)$:

$$f(x) = \sum_i \sum_j a_{ij} x_i x_j$$

2. write out the gradient:

$$\begin{aligned}
\frac{\partial y}{\partial x_1} &= \frac{\partial(a_{11}x_1^2)}{\partial x_1} + a_{12}x_2 + ... + a_{1n}x_n + a_{21}x_2 + ... + a_{n1}x_n \\
&= 2a_{11}x_1 + \sum_{j=2}^{n} a_{1j}x_j + \sum_{i=2}^{n} a_{1i}x_i \\
&= \sum_{j=1}^{n} a_{1j}x_j + \sum_{i=1}^{n} a_{i1}x_i \\
&= (Ax)_1 + (A^T x)_1 \\
\frac{\partial y}{\partial x_i} &= (Ax)_i + (A^T x)_i \\
\frac{\partial y}{\partial x} &= \nabla_x f(x) = Ax + A^T x
\end{aligned}$$

   - an intuition check is to consider the problem in a single dimension:
     - ie. when $n = 1$, $f(x) = xax = ax^2$ and $\frac{\partial f(x)}{\partial x} = 2ax$
     - when A is symmetric, the gradient is analogously just $2Ax$

- derivative of a scalar with respect to a matrix:
  - given a scalar y and a matrix $A \in \mathbb{R}^{m \times n}$, the derivative is given by:

$$\nabla_A y = \begin{bmatrix} \frac{\partial y}{\partial a_{11}} & \cdots & \frac{\partial y}{\partial a_{1n}} \\ \vdots & \ddots & \vdots \\ \frac{\partial y}{\partial a_{m1}} & \cdots & \frac{\partial y}{\partial a_{mn}} \end{bmatrix}$$

  - like the gradient, the i, jth element of $\nabla_A y$ tells us how small changes in a_{ij} affect y
  - this layout is called **denominator layout** notation, in which the dimensions of $\nabla_A y$ and A are the same
    - in **numerator layout**, the dimensions are transposed
- derivative of a vector with respect to a vector:
  - given $y \in \mathbb{R}^n$ as a function of $x \in \mathbb{R}^m$, the derivative of y with respect to x would be used as follows:

$$\Delta y_i = \nabla_x y_i \cdot \Delta x$$

  - thus, the derivative J should be an $n \times m$ matrix as follows:

$$J = \begin{bmatrix} (\nabla_x y_1)^T \\ \vdots \\ (\nabla_x y_n)^T \end{bmatrix} = \begin{bmatrix} \frac{\partial y_1}{\partial x_1} \cdots \frac{\partial y_1}{\partial x_m} \\ \vdots \quad \ddots \quad \vdots \\ \frac{\partial y_n}{\partial x_1} \cdots \frac{\partial y_n}{\partial x_m} \end{bmatrix}$$

  - like the gradient, we can see how small changes in x affect y as follows:

$$\Delta y \approx J \Delta x$$

    * J is called the **Jacobian** matrix
  - since in the denominator layout, the denominator vector changes along rows (instead of along columns, as in the Jacobian):

$$J = (\nabla_x y)^T = (\frac{\partial y}{\partial x})^T$$

- the **Hessian** matrix of a function $f(x)$ is a square matrix of second-order partial derivatives of f as follows:

$$H = \begin{bmatrix} \frac{\partial f}{\partial x_1^2} & \frac{\partial f}{\partial x_1 \partial x_2} & \cdots & \frac{\partial f}{\partial x_1 \partial x_n} \\ \frac{\partial f}{\partial x_2 \partial x_1} & \frac{\partial f}{\partial x_2^2} & \cdots & \frac{\partial f}{\partial x_2 \partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f}{\partial x_m \partial x_1} & \frac{\partial f}{\partial x_m \partial x_2} & \cdots & \frac{\partial f}{\partial x_m^2} \end{bmatrix}$$

  - the Hessian is denoted as $\nabla_x(\nabla_x f(x))$ or equivalently $\nabla_x^2 f(x)$

Chain Rule

- the **chain rule** for vector valued functions:
  - in the denominator layout, the chain rule runs from right to left
  - if $x \in \mathbb{R}^m, y \in \mathbb{R}^n, z \in \mathbb{R}^p$ and $y = f(x)$ for $f : \mathbb{R}^m \to \mathbb{R}^n$ and $z = g(y)$ for $g : \mathbb{R}^n \to \mathbb{R}^p$, then:

$$\nabla_x z = \nabla_x y \nabla_y z$$
$$\frac{\partial z}{\partial x} = \frac{\partial y}{\partial x} \frac{\partial z}{\partial y}$$

    * $\nabla_x z$ should have dimensionality $\mathbb{R}^{m \times p}$

    - since $\nabla_x y \in \mathbb{R}^{m \times n}$ and $\nabla_y z \in \mathbb{R}^{n \times p}$, the operations are dimensionally correct
- composing the chain rule:
  - intuitively, a small change Δx affects Δz through the Jacobian $(\nabla_x z)^T$:

$$\Delta z \approx (\nabla_x z)^T \Delta x$$

  - then, through composition:

$$\begin{aligned} \Delta y &\approx (\nabla_x y)^T \Delta x \\ \Delta z &\approx (\nabla_y z)^T \Delta y \\ \Delta z &\approx (\nabla_y z)^T (\nabla_x y)^T \Delta x \end{aligned}$$

  - thus reduces to the right to left chain rule:

$$\begin{aligned} (\nabla_x z)^T &= (\nabla_y z)^T (\nabla_x y)^T \\ \nabla_x z &= \nabla_x y \nabla_y z \end{aligned}$$

Tensors

- we may need to take a derivative that is more than 2-dimensional:
  - eg. the derivative of a vector with respect to a matrix would be a 3-dimensional **tensor**
    - a tensor is an array with more than two axes
  - if $z \in \mathbb{R}^p$ and $W \in \mathbb{R}^{m \times n}$ then $\nabla_W z$ is a 3-dimensional tensor with shape $\mathbb{R}^{m \times n \times p}$
    - each $m \times n$ slice is the matrix derivative $\nabla_W z_i$

Discussion Problems

- ex. show the following properties for matrices:
  1. if $b^T A b > 0 \ \forall \ b \in \mathbb{R}^n$, then all eigenvalues of A are positive:

$$\begin{aligned} A v_i &= \lambda_i v_i \\ v_i^T A v_i &= \lambda_i v_i^T v_i \\ v_i^T A v_i &= \lambda_i ||v_i||_2^2 > 0 \\ &\therefore \ ||v_i||_2^2 > 0, \lambda_i > 0 \end{aligned}$$

  - this is a positive definite matrix

2. if $A \in \mathbb{R}^{n \times n}$ is an orthogonal matrix, then all eigenvalues of A have norm 1:

$$\begin{aligned} Av_i &= \lambda_i v_i \\ A^T A v_i &= \lambda_i A^T v_i \\ v_i &= \lambda_i A^T v_i \\ ||v_i||_2^2 &= |\lambda_i|^2 ||A^T v_i||_2^2 \\ &= |\lambda_i|^2 (A^T v_i)^T (A^T v_i) \\ &= |\lambda_i|^2 v_i^T A A^T v_i \\ &= |\lambda_i|^2 ||v_i||_2^2 \\ &\therefore \ |\lambda_i| = 1 \end{aligned}$$

3. If $A \in \mathbb{R}^{m \times n}$ is a matrix with rank r, then $\sigma_i(A) = \lambda_i^{\frac{1}{2}}(AA^T)$:

$$\Sigma\Sigma^T = diag(\sigma_1^2, \dots, \sigma_n^2)$$

$$\begin{aligned} A &= U\Sigma V^T \\ AA^T &= (U\Sigma V^T)(U\Sigma V^T)^T \\ &= U\Sigma V^T V \Sigma^T U^T \\ &= U\Sigma\Sigma^T U^T \\ &= U diag(\sigma_1^2, \dots, \sigma_n^2) U^T \\ &\therefore \ \sigma_i(A) = \lambda_i^{\frac{1}{2}}(AA^T) \end{aligned}$$

   - producing an eigendecomposition of AA^T