

Temporal Learning, Modeling and Adaptation

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1 Time Series Review

1.1 Stochastic Processes

Temporal Information Processing?

- First interpretation: the **processing of information that has a time structure**, i.e., time series
- Time series (TS): a time-ordered sequence of scalar or vector values X_t
- The temporal structure determines the behavior of X_t and must be taken into account to model it
- Second interpretation: the **temporal processing of information**
- Even if they do not have a temporal structure, data are (almost always) generated sequentially
- Examples: streaming data, on-line learning
- In both cases we get back to Machine Learning (although with different objectives)
 - Clearly so in on-line learning
 - After some roundabouts in practical TS modelling
- We deal first with time structured data

Time Series Contexts

- Two different TS origins:
 - **Stochastic generation**: the observed TS is a realization of a **stochastic process**
 - **Dynamical system evolution**: the observed TS is the trajectory of the solution of a continuous or discrete dynamical system (DS) from given initial conditions
- Different worlds (stochastic vs deterministic) but sometimes are hard to tell them apart
- Very different tools and perspectives
 - For stochastic TS we worry about **stationarity, ergodicity, spectral densities**; linear models and short term prediction are the main goals
 - For DS we worry about **sinks, sources, stability, attractors, chaos**; the main goal is non-linear long term behavior, often very sensible to initial conditions
- We begin with (general) stochastic processes and then briefly review the (much simpler) ARMA models

Basic Tools

- Probability Space: triplet made up of a set Ω , a subset \mathcal{A} of 2^Ω and a probability P defined in \mathcal{A}

- We associate \mathcal{A} with the events to which we can assign a probability
- If Ω is discrete, usually $\mathcal{A} = 2^\Omega$ (i.e., all possible subsets of Ω)
- Two subsets $A, B \in \mathcal{A}$ are **independent** if $P(A \cap B) = P(A)P(B)$
- Random variable: a function $X : \Omega \rightarrow \mathbf{R}$
 - As such X is deterministic; it is its arguments that are random
- Mean of X : $\bar{X} = \mu_x = E_P[X]$
- If $\mu_X < \infty$, its variance is $\text{var}(X) = E_P[(X - \mu_X)^2] = E_P[X^2] - \mu_X^2$
- The order k moment of X is $E_P[X^k]$

Computing Expectations

- What do we mean by $E_P[X]$?
- In simple cases it is clear:
 - If Ω discrete, $E_P[X] = \sum X(\omega)P(\{\omega\})$
 - If X takes discrete values $\{x_n\}$, $E_P[X] = \sum x_n P(\{\omega : X(\omega) = x_n\})$
- In general, one defines the expectation of X in terms of the **distribution function** of X

$$F(x) = F_X(x) = P(\{\omega : X(\omega) \leq x\})$$

- Clearly $F(x)$ is increasing
- If x is one-dimensional and F is derivable, $F'(x) = f(x)$ is its **density**
- Then for a general one-dimensional continuous X , $E[X]$ is defined as a **Stieltjes integral** of x with respect to F : $E[X] = \int x dF_X(x) = \int x dF(x)$
 - If F is differentiable, $E[X] = \int x f(x) dx$
 - We can also define $E_X[g(X)] = E[g(X)] = \int g(x) dF(x)$

Joint Distribution Function

- Given two r.v. X, Y their **joint distribution** $F(x, y)$ is defined as

$$\begin{aligned} F(x, y) &= F_{X,Y}(x, y) = P(\{\omega : X(\omega) \leq x, Y(\omega) \leq y\}) \\ &= P(\{X(\omega) \leq x\} \cap \{Y(\omega) \leq y\}) \end{aligned}$$

- Then $\int_{y=-\infty}^{\infty} dF(x, y) = F(x, \infty) = P(\{\omega : X(\omega) \leq x\}) = F_X(x)$
- If $F(x, y)$ is differentiable, $\frac{\partial^2 F}{\partial x \partial y} = f(x, y)$ is the joint density
- We can define $E_{X,Y}[g(X, Y)] = \int g(x, y) dF(x, y)$ also as a Stieltjes integral
 - If $F(x, y)$ differentiable, $\int g(x, y) dF(x, y) = \int g(x, y) f(x, y) dx dy$

- X, Y are said to be **independent** if the subsets $\{x_1 \leq x \leq x_2\}$ and $\{y_1 \leq y \leq y_2\}$ are independent
 - Then $F(x, y) = F_X(x)F_Y(y)$
- Similarly, if X_1, \dots, X_K are random variables, we can define $F(x_1, \dots, x_K) = P(\{\omega : X_k(\omega) \leq x_k, k = 1, \dots, K\})$

Stochastic Processes

- A **stochastic/random process** (SP) is a family $\{X_t\}$ of random variables on a common probability space (Ω, \mathcal{A}, P)
 - We will consider discrete time: $\{t\} = \{\dots, -1, 0, 1, \dots\}$
 - If we fix a $\omega_0 \in \Omega$, a **sample path** or **realization** of a SP is the sequence $\{x_t = X_t(\omega_0)\}$
- Examples of SPs
 - **White noise:** X_t are independent variables with 0 mean and finite variance
 - **Brownian Motion:** $X_0 \equiv 0$, the increments $X_t - X_s$ are independent, $X_t - X_s = N(0, \sqrt{t-s} I)$
 - **Markov models:** $\Omega = \{1, \dots, N\}$ is discrete and $P(X_{t+1} = j | X_t = i, X_{t-1} = i_{t-1}, \dots, X_{t-k} = i_{t-k}) = P(X_{t+1} = j | X_t = i)$
 - * $p_{ij} = P(X_{t+1} = j | X_t = i)$ is the **transition matrix**
- Kolmogorov's Theorem ensures the existence of underlying SPs
- But if the different X_t behave differently, it will be difficult to say much about them

Stationarity

- We can define the joint distributions $F_\tau(x_1, \dots, x_K)$ for $\tau = (t_1, \dots, t_K)$ of the SP X_t as $F_\tau(x_1, \dots, x_K) = P(\{\omega : X_{t_k}(\omega) \leq x_k, k = 1, \dots, K\})$
- The SP X_t is **strictly stationary** (SS) if for all K, τ and h we have for $\tau + h = (t_1 + h, \dots, t_K + h)$

$$F_\tau(x_1, \dots, x_K) = F_{\tau+h}(x_1, \dots, x_K)$$

- If X_t is SS, $\mu_t = \int x dF_t(x) = \int x dF_{t+h}(x) = \mu_{t+h} \forall h$
- The **autocovariances** of X_t are

$$\begin{aligned} \gamma(r, s) &= \text{cov}(X_r, X_s) = E[(X_r - \mu_r)(X_s - \mu_s)] \\ &= \int (x - \mu_r)(x' - \mu_s) dF_{r,s}(x, x'), \end{aligned}$$

- If X_t is SS, $\gamma(r, s) = \gamma(r + h, s + h) = \gamma(r - s, 0) \forall r, s, h$,

Stationarity II

- Also $\gamma(r, s) = \gamma(s, r)$
- SS is very desirable, but perhaps too restrictive
- We relax it to just **stationarity** (S) (or weakly/second order stationarity) if we simply impose

$$\mu_t = \mu, \quad \gamma(t+h, t) = \gamma(h, 0) \quad \forall t, h$$

We just write $\gamma(h)$ instead of $\gamma(h, 0)$

- In particular $\gamma(0) = \text{var}[X_t]$ for all t
- Moreover, if $\mu_t = 0$, $\gamma(h) \leq \gamma(0)$
- If we define the **autocorrelations** $\rho(h) = \gamma(h)/\gamma(0)$, we have $\rho(h) \leq 1$

Ergodicity

- The time series $\{x_t\}$ given as a realization of a S SP X_t is the only information that we have if we want to compute the statistics of all X_t
- Ergodicity makes possible to estimate moments of X_t from the time series values
- An intuitive idea is to estimate μ by the mean $\hat{\mu}_k = \frac{1}{2k+1} \sum_{-k}^k x_t$, for considering the RV $M_K = \frac{1}{2k+1} \sum_{-k}^k X_t$, we have

$$E[M_K] = \frac{1}{2k+1} \sum_{-k}^k E[X_t] = \frac{1}{2k+1} \sum_{-k}^k \mu = \mu$$

- If the variance σ_k^2 of $\hat{\mu}_k$ tends to 0, $\hat{\mu}_k$ **tends to μ in MSE** and we say that X_t is **mean-ergodic**
- **Slutsky's theorem:** A S SP X_t with covariance $\gamma(k)$ it is mean-ergodic iff $\lim_{k \rightarrow \infty} \frac{1}{k+1} \sum_0^k \gamma(j) = 0$

Covariance Ergodicity

- Assuming $\mu = 0$, the intuitive variance estimation is now

$$\hat{v}_k = \frac{1}{2k+1} \sum_{-k}^k x_t^2,$$

which is the mean of the SP X_t^2

- Now if X_t is a S SP, so is X_t^2 and we can apply again Slutsky's theorem
- The covariance $\gamma^2(k)$ of X_t^2 is $\gamma^2(k) = E[X_k^2 X_0^2] - E[X_0^2]^2$
- The Slutsky's condition for **covariance ergodicity** is now $\lim_{k \rightarrow \infty} \frac{1}{k+1} \sum_0^k \gamma^2(j) = 0$ or, equivalently,

$$\lim_{k \rightarrow \infty} \frac{1}{k+1} \sum_0^k E[X_j^2 X_0^2] = E[X_0^2]^2$$

1.2 Basic TS Models

AR and MA Models

- An **autoregressive** (AR) model of order p is a SP X_t with 0 mean where $X_t = \sum_1^p \phi_j X_{t-j} + \epsilon_t$, with ϵ_t white noise with variance σ^2
- If B denotes the **time delay** operator $BX_t = X_{t-1}$, we can write the above as

$$\epsilon_t = X_t - \sum_1^p \phi_j X_{t-j} = (I - \sum_1^p \phi_j B^j) X_t = \Phi(B) X_t$$

- A **moving average** (MA) model of order q is a SP X_t where $X_t = \epsilon_t + \sum_1^q \theta_j \epsilon_{t-j}$, with ϵ_t again white noise
- Just as before, we can write a MA (q) SP X_t as

$$X_t = \epsilon_t + \sum_1^q \theta_j \epsilon_{t-j} = (I + \sum_1^q \theta_j B^j) \epsilon_t = \Theta(B) \epsilon_t$$

Stationarity of AR and MA Models

- It is easy to see that if X_t is a S SP, $Y_t = \sum_0^q \theta_j X_{t-j}$ is also a S SP
- Thus any MA (q) SP is S
- If the series $\sum_0^\infty |\theta_j|$ converges and X_t is a S SP, the SP $Y_t = \sum_0^\infty \theta_j X_{t-j} = \sum_0^\infty \theta_j B^j X_t$ is also S
- What about AR (p) processes?
- If X_t is $AR(1)$ we have $\epsilon_t = X_t - \phi X_{t-1} = (1 - \phi B)X_t$ or, formally, $X_t = (1 - \phi B)^{-1} \epsilon_t = \sum_0^\infty \phi^j B^j \epsilon_t$
- If $|\phi| < 1$ the series converges; thus an $AR(1)$ process is S if $|\phi| < 1$ (in fact iff)
- Notice that the root $1/\phi$ of $\Phi(z) = 1 - \phi z$ lies outside the unit circle
- For a general AR (p) SP X_t we have formally $X_t = (\Phi(B))^{-1} \epsilon_t$, and **we can invert $\Phi(B)$ into a convergent series if the polynomial $\Phi(z)$ has all its roots outside the unit circle**
- Thus an AR (p) process X_t is S if(f) $\Phi(z)$ has all its roots outside the unit circle

ARMA Models

- An **ARMA** (p, q) model is a SP X_t s.t.

$$X_t = \sum_1^p \phi_i X_{t-i} + \sum_1^q \theta_j \epsilon_{t-j} + \epsilon_t,$$

with ϵ_t white noise

- We can rewrite the above as $\epsilon_t + \sum_1^q \theta_j \epsilon_{t-j} = X_t - \sum_1^p \phi_i X_{t-i}$, i.e.

$$\Theta(B)\epsilon_t = \Phi(B)X_t$$

for some polynomials Φ, Θ

- Formally we have $X_t = \Phi(B)^{-1}\Theta(B)\epsilon_t$, which we can express as

$$X_t = \sum_0^\infty \gamma_j B^j \Theta(B)\epsilon_t = \sum_0^\infty \delta_i B^i \epsilon_t$$

if $\Phi(z)$ has all its roots outside the unit circle

- Thus an ARMA (p, q) process X_t is S if(f) $\Phi(z)$ has all its roots outside the unit circle

Covariance Functions

- Q1: How easy is to identify an ARMA process?
 - Right now this a too general question
- Q2: are there simple ways to characterize ARMA processes?
 - Yes: through their covariances
- In fact, covariances are sort of a **signature** of S SPs
- **Theorem:** a function $K : Z \rightarrow C$ is the autocovariance function of a (possibly complex) S TS iff it is **Hermitian and semi-definite positive**, i.e.,
 - $K(h) = \overline{K(-h)}$ and
 - For any $n \geq 0$ and $a \in C^n$, $a^t K(n) a \geq 0$, where $K(n)$ is the $n \times n$ matrix $K(n)_{ij} = K(i - j)$
- We can thus focus our attention on Hermitian and semi-definite positive functions

Spectral Covariance Representation

- **Riesz–Herglotz Theorem:** a function $\gamma : Z \rightarrow C$ is hermitian and semi-definite positive (i.e., an autocovariance function) iff

$$\gamma(h) = \int_{-\pi}^{\pi} e^{ih\omega} dF(\omega)$$

with F a right-continuous, non decreasing function on $[-\pi, \pi]$ with $F(-\pi) = 0$

- Such an F is called the **spectral distribution** of γ
- If we can write $F(\omega) = \int_{-\pi}^{\omega} f(u) du$, we say that f is the **spectral density** of γ and then $\gamma(h) = \int_{-\pi}^{\pi} e^{ih\omega} f(\omega) d\omega$
- Notice that then $f(\omega) = F'(\omega) \geq 0$

- With (considerable) more work we can arrive at a spectral representation of a S SP X_t

Spectral Densities

- Spectral densities are much easier to handle
- If $\gamma(h)$ is summable (i.e., $\sum_h |\gamma(h)| < \infty$), Fourier series theory implies that

$$f(\omega) = \frac{1}{2\pi} \sum_{-\infty}^{\infty} \gamma(h) e^{ih\omega}$$

- An immediate consequence is that an absolutely summable $\gamma(h)$ is the autocovariance function of a S TS X_t iff $f(\omega) = \sum_{-\infty}^{\infty} \gamma(h) e^{ih\omega} > 0$
- Moreover, if X_t is real, f is symmetric
- Thus, S TSs with “simple” γ should have spectral densities easy to compute
- For instance, if ϵ_t is white noise with variance σ^2 , its spectral density is $\sigma^2/2\pi$
- This is also the case for MA and (with more work) AR processes

Autocovariances of MA Processes

- MA processes have the simplest autocovariances:
If X_t is a zero-mean S SP whose autocovariances verify $\gamma(h) = 0$ if $|h| > q$, then it is a MA(q) process
- More generally, if $\sum_0^{\infty} |\theta_k| < \infty$,

$$X_t = \sum_0^{\infty} \theta_k \epsilon_{t-k}$$

is called a MA(∞) process

- It is relatively easy to check that its autocovariances verify

$$\gamma(h) = \sigma^2 \sum_0^{\infty} \theta_j \theta_{j+|h|}$$

Autocovariances of AR Processes

- The situation is more complicated for AR(p) processes
- Their covariances cannot be written in closed form unless p is small
- Usually they are all non zero
- To get them, recall that if X_t is AR(p) and $\Phi(z)$ has all its roots outside the unit circle, then we can write $\Phi(B)X_t = \epsilon_t$

- Multiplying both sides by X_{t-k} and taking expectations, we can get recurrence relations for $\gamma(k)$
- Easy exercise: compute them for $X_t = \phi X_{t-1} + \epsilon_t$, $\phi < 1$
- Nevertheless, AR and MA spectral densities are simpler to find

Spect. Densities of AR and MA Processes

- If we have $Y_t = \sum_{-\infty}^{\infty} \psi_j Z_{t-j} = \sum_{-\infty}^{\infty} \psi_j B^j Z_t$, with ψ_j real and Z_t is S with zero mean and spectral density (spd) f_Z , then Y_t is S with spectral distribution

$$F_Y(\omega) = \int_{-\pi}^{\omega} \left| \sum_{-\infty}^{\infty} \psi_j e^{-iju} \right|^2 f_Z(u) du = \int_{-\pi}^{\omega} \left| \sum_{-\infty}^{\infty} \psi_j (e^{-iu})^j \right|^2 f_Z(u) du$$

$$\text{and } f_Y(\omega) = F'_Y(\omega) = \left| \sum_{-\infty}^{\infty} \psi_j (e^{-i\omega})^j \right|^2 f_Z(\omega)$$

- Since for an AR(p) X_t we have $\epsilon_t = \Phi(B)X_t$, it follows that

$$\frac{\sigma^2}{2\pi} = |\Phi(e^{-i\omega})|^2 f_X(\omega) \Rightarrow f_X(\omega) = \frac{\sigma^2}{2\pi} \frac{1}{|\Phi(e^{-i\omega})|^2}$$

- And since for a MA(q) X_t we have $X_t = \Theta(B)\epsilon_t$, its spd is $f_X(\omega) = \frac{\sigma^2}{2\pi} |\Theta(e^{-i\omega})|^2$

Spectral Densities of ARMA Processes

- For an ARMA(p, q) X_t we have $Y_t = \Phi(B)X_t = \Theta(B)\epsilon_t$, and putting together the previous equalities, we get

$$f_Y(\omega) = |\Phi(e^{-i\omega})|^2 f_X(\omega) = \frac{\sigma^2}{2\pi} |\Theta(e^{-i\omega})|^2$$

- Working things out we arrive at a rational spectral density

$$f_X(\omega) = \frac{\sigma^2}{2\pi} \frac{|\Theta(e^{-i\omega})|^2}{|\Phi(e^{-i\omega})|^2} = \frac{\sigma^2}{2\pi} \left| \frac{\Theta(e^{-i\omega})}{\Phi(e^{-i\omega})} \right|^2$$

- Since rational functions (and polynomials) are dense in $C([-\pi, \pi])$, a process with a symmetric continuous spd can be approximated in an appropriate sense by ARMA(p, q) or MA(q) processes
- But this has more theoretical than practical interest

ARIMA Models

- In general, time series are not stationary, with a typical instance being SP of the form $X_t = m_t + s_t + Y_t$, with m_t the **trend**, s_t a (periodic) **seasonal** component and Y_t a S SP

- The removal of m_t is problem dependent, with a frequent choice being the application of some power Δ^d of the difference operator $\Delta X_t = \Delta_1 X_t = X_t - X_{t-1}$
- A seasonal component with period S (i.e., $s_t = s_{t+S}$) can be removed applying the operator Δ_S , i.e. $\Delta_S X_t = X_t - X_{t-S}$
- An ARIMA (p, d, q) model is a SP X_t such that $\Delta^d X_t$ is an ARMA (p, q) model
- A seasonal ARIMA $(p, d, q) \times (P, D, Q)_S$ SP X_t can be formally expressed as

$$\Phi(B^S)\Phi(B)\Delta_S^D\Delta^d(X_t) = \Theta(B^S)\Theta(B)\epsilon_t$$

ARX and NARX Models

- Thus things get progressively more complicated and drift towards **system identification**, i.e., to use statistical methods to build mathematical models of dynamical systems from measured data
- Moreover, there may be some other inputs U_t that we may want to incorporate to our model
- In an autoregressive with exogenous inputs (ARX) model we assume that our target X_t has the form

$$X_t = \sum_1^D \phi_j X_{t-j} + \sum_0^{D'} \theta_{j'} U_{t-j'} + \epsilon_t$$

- Issues such as stationarity or ergodicity start to fade ...
- In a non linear ARX (NARX) the target X_t is a non linear function of the $X_{t-j}, U_{t-j'}$:

$$X_t = \Phi(X_{t-1}, \dots, X_{t-D}, U_t, U_{t-1}, \dots, U_{t-D'}) + \epsilon_t$$

- Besides being reasonable by themselves, they also appear when studying dynamical systems

2 Dynamical Systems

2.1 Linear Differential Equations

From AR to Dynamical Systems

- If in an AR process we impose $\epsilon_t = 0$ we are left with the difference equation $x_t = \sum_1^p \alpha_j x_{t-j}$
- In general, we say that a system $X_t \in \mathbf{R}^d$ follows a discrete differential equation if $X(t+1) = x_{t+1} = F(x_t) = F(X(t))$
- In turn writing $X'(t) \simeq X(t+1) - X(t) = F(X(t)) - X(t) = G(X(t))$, we arrive to a system of differential equations $X' = G(X)$

- Differential equation systems have behind a rich (and sometimes difficult) theory
- Basic examples: linear systems

Linear Systems

- An **autonomous linear system** is given by

$$X' = AX, \quad X(0) = x_0 \quad (1)$$

for a $d \times d$ matrix A

- Basic example: (homogeneous) harmonic oscillator $x'' + ax' + bx = 0$
- Setting $y = x'$ we have $x' = y$, $y' = -bx - ay$; that is, for $X = (x, y)^t$, we have

$$X' = \begin{pmatrix} 0 & 1 \\ -b & -a \end{pmatrix} X = AX$$

- The **exponential** of a matrix B is $e^B = \sum_0^\infty \frac{B^n}{n!}$
- The general solution of (1) when $X(0) = x_0$ is $X(t) = e^{tA}x_0$

The Linearity Principle

- The eigenanalysis of A is the basic tool to study linear systems:
if $Av_0 = \lambda v_0$, then $V(t) = e^{\lambda t}v_0$ is a solution with $V(0) = v_0$
- Now assume that λ_1, λ_2 are distinct eigenvalues of A with eigenvectors v_1, v_2 , and let $x_0 = \alpha_1 v_1 + \alpha_2 v_2$
- Then we can find the solution of $X' = AX$ with $X(0) = x_0$ by writing

$$X(t) = \alpha_1 e^{\lambda_1 t} v_1 + \alpha_2 e^{\lambda_2 t} v_2$$

- This is a particular case of the **Linearity Principle**:

If $Y_1(t), Y_2(t)$ are solutions of $X' = AX$ and $Y_1(0), Y_2(0)$ are linearly independent, then $X(t) = \alpha Y_1(t) + \beta Y_2(t)$ is the unique solution that satisfies $X(0) = \alpha Y_1(0) + \beta Y_2(0)$

- Simplest linear systems: **planar** systems in \mathbf{R}^2

Higher Dimensional Systems

- In principle for any $d \times d$ matrix A , $e^{tA}x_0$ yields the (unique) solution of $X' = AX$ with $X(0) = x_0$
- However the eigenstructure of a general A is more complicated than in the planar case
- Simplest situation: A has d **distinct eigenvalues**
- Then A can be transformed as $M = TAT^{-1}$ into a matrix M made up of a diagonal block and a series of 2-dimensional diagonal blocks $\begin{pmatrix} \alpha & \beta \\ -\beta & \alpha \end{pmatrix}$

- The structure of M when there are repeated eigenvalues is given by the (more complicated) **Jordan form** of A
- However, matrices with distinct eigenvalues are what is to be expected:

*The subset of matrices with d distinct eigenvalues is an **open and dense** subset of the set of $d \times d$ matrices*

Non Autonomous Linear Systems

- The general form of a non autonomous linear system is $X' = A(t)X$, with $A(t)$ a time varying $d \times d$ matrix
- A general discussion of such systems is not possible; a simpler situation is that of **forced linear system** (FS)

$$X' = AX + G(t), \quad X(0) = x_0$$

- The time independent system $X' = AX$ is the **homogeneous equation** (HE)
- If we know a particular solution Z of the FS and X is a solution of the HE, $Y = Z + X$ is another solution of the FS with initial condition $X(0) + Z(0)$
- Conversely, if Y, Z are solutions of the FS, $X = Y - Z$ is a solution of the HE with $X(0) = Y(0) - Z(0)$
- Since $e^{tA}x_0$ gives the general solution of the HE, **it is enough to find a particular solution to the FS**

Variation of Parameters

- Given the FS $X' = AX + G(t)$, $X(0) = x_0$, a first try to solve it is to guess a particular solution; this is the method of **undetermined coefficients**
- However such a guess is not usually easy; the method of **variation of parameters** yields a (theoretical) general solution
- The solution of the above FS for $X(0) = x_0$ is given by

$$X(t) = e^{tA} \left(x_0 + \int_0^t e^{-sA} G(s) ds \right)$$

- The difficulty is, of course, to compute the integral!!

2.2 Planar Systems

Planar Systems

- A planar system is an autonomous linear system in \mathbf{R}^2 , that is a function $X(t) \in \mathbf{R}^2$ such that

$$X' = AX, \quad X(0) = x_0$$

- Solution again given as $X(0) = x_0$ is $X(t) = e^{tA}x_0$
- If $A = \text{diag}(\lambda_1, \lambda_2)$ then

$$e^{tA} = \begin{pmatrix} e^{t\lambda_1} & 0 \\ 0 & e^{t\lambda_2} \end{pmatrix}$$

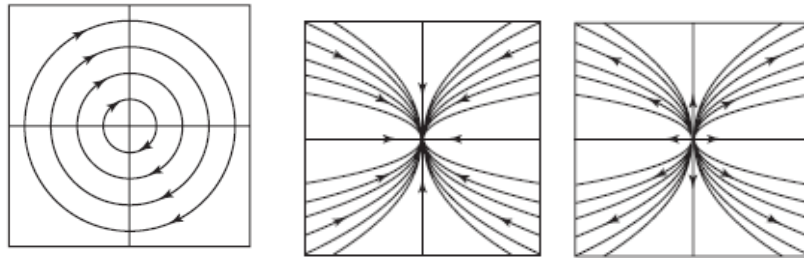
- Now A is a 2×2 matrix and its eigenanalysis is quite simple
- Thus, planar systems can be studied quite exhaustively

Phase Portraits

- The goal in the study of dynamical systems is often to understand their asymptotic behavior
- This is depicted using **phase portraits**
- The phase portrait of a planar system is a picture of a collection of representative solution curves in \mathbf{R}^2 , which we call the **phase space**, for which a general idea of their evolution can be derived
- **Critical points** (and **equilibrium solutions**) arise when $0 = X' = AX$, with 0 the only critical point if $\det A \neq 0$

Examples of Phase Portraits

- Here are some examples associated at particular planar systems



- We can arrive to a complete understanding of the behavior of planar systems mapping the eigenanalysis of A into phase portraits

Planar Systems in Canonical Form

- Eigen values of a 2×2 matrix A : either two distinct real eigenvalues, or two repeated real eigenvalues, or two complex conjugate eigenvalues
- A 2×2 matrix A is in **canonical form** if it has one of the following forms:

$$\begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{pmatrix}, \begin{pmatrix} \alpha & \beta \\ -\beta & \alpha \end{pmatrix}, \begin{pmatrix} \lambda & 1 \\ 0 & \lambda \end{pmatrix}$$

- We will split the analysis of these cases according to the eigenvalues of A :

- A has two distinct real eigenvalues, i.e., the first matrix with $\lambda_1 \neq \lambda_2$
- A has two complex conjugate eigenvalues, i.e., the second matrix
- A has a single repeated real eigenvalue, i.e., the first matrix with $\lambda_1 = \lambda_2$ or the third matrix
- These cases will determine the limit behavior of the solutions of a general $X' = AX$

Real Distinct Eigenvalues I: Saddle Points

- If there are two non zero, distinct real eigenvalues λ_1, λ_2 , we have

$$X(t) = \exp \left(t \begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{pmatrix} \right) x_0 = \begin{pmatrix} e^{\lambda_1 t} & 0 \\ 0 & e^{\lambda_2 t} \end{pmatrix} x_0 = \begin{pmatrix} \alpha e^{\lambda_1 t} \\ \beta e^{\lambda_2 t} \end{pmatrix}$$

- There are three important cases: i) $\lambda_1 < 0 < \lambda_2$, ii) $\lambda_1 < \lambda_2 < 0$, iii) $0 < \lambda_1 < \lambda_2$
- In the case $\lambda_1 < 0 < \lambda_2$,
 - The solutions $\alpha e^{\lambda_1 t}$ tend to 0 as $t \rightarrow \infty$: they lie in the **stable** line
 - The solutions $\beta e^{\lambda_2 t}$ tend away from 0 as $t \rightarrow \infty$: they lie in the **unstable** line
 - The solutions for $\alpha, \beta \neq 0$ tend to $\pm\infty$ getting closer to the unstable line
- The origin is the only equilibrium point, which we call a **saddle point**

Real Distinct Eigenvalues II: Sinks

- When $\lambda_1 < \lambda_2 < 0$, both solutions $\alpha e^{\lambda_1 t}, \beta e^{\lambda_2 t} \rightarrow 0$ when $t \rightarrow \infty$
- For a general solution $X(t) = \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} \alpha e^{\lambda_1 t} \\ \beta e^{\lambda_2 t} \end{pmatrix}$, writing $x(t) = \alpha_1 e^{\lambda_1 t}$, $y(t) = \alpha_2 e^{\lambda_2 t}$, we have

$$\frac{dy}{dx} = \frac{y'}{x'} = \frac{\lambda_2 \alpha_2 e^{\lambda_2 t}}{\lambda_1 \alpha_1 e^{\lambda_1 t}} = \frac{\lambda_2 \alpha_2}{\lambda_1 \alpha_1} e^{(\lambda_2 - \lambda_1)t}$$

which tends to $\pm\infty$ when $\alpha_2 \neq 0$

- Thus the trajectories **tend to 0 tangentially to the Y axis**
- The origin, again the only equilibrium point, is now called a **sink**

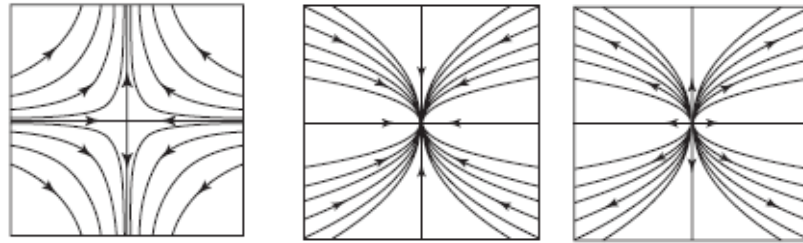
Real Distinct Eigenvalues III: Sources

- When $0 < \lambda_2 < \lambda_1$, a similar analysis yields
 - Both solutions $\alpha e^{\lambda_1 t}, \alpha e^{\lambda_2 t} \rightarrow \infty$ when $t \rightarrow \infty$
 - Writing as before $x(t) = \alpha_1 e^{\lambda_1 t}$, $y(t) = \alpha_2 e^{\lambda_2 t}$, we have that $\frac{y'}{x'}$ tends to 0 when $\alpha_2 \neq 0$
- Thus the trajectories **tend to ∞ away from 0 tangentially to the Y axis initially and becoming “horizontal” as $t \rightarrow \infty$**

- The origin, again the only equilibrium point, is now called a **source**
- When one of the eigenvalues, say $\lambda_1 = 0$, the X -axis defines an equilibrium line
- The other solutions tend to ∞ away from the axis if $\lambda_2 > 0$ or to 0 otherwise

Saddles, Sinks and Sources

- We depict saddles (left), sinks and sources (right) for planar systems in canonical form



From Hirsch et al., *Differential equations dynamical systems and an introduction to chaos*.

Complex Eigenvalues

- When $A = \begin{pmatrix} \alpha & \beta \\ -\beta & \alpha \end{pmatrix}$ the eigenvalues are $\alpha \pm i\beta$
- This yields two real solutions

$$e^{\alpha t} \begin{pmatrix} \cos \beta t \\ -\sin \beta t \end{pmatrix}, \quad e^{\alpha t} \begin{pmatrix} \sin \beta t \\ \cos \beta t \end{pmatrix}$$

and the general solution

$$X(t) = c_1 e^{\alpha t} \begin{pmatrix} \cos \beta t \\ -\sin \beta t \end{pmatrix} + c_2 e^{\alpha t} \begin{pmatrix} \sin \beta t \\ \cos \beta t \end{pmatrix}$$

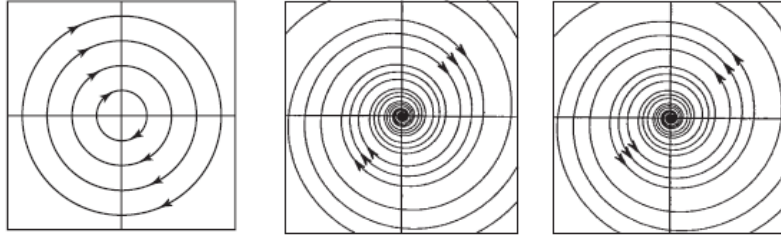
- If $\alpha = 0$, we have $\|X(t)\|^2 = c_1^2 + c_2^2$, i.e., the solutions **cycle** around 0
- If $\alpha \neq 0$, we get spirals that turn towards the origin when $\alpha < 0$ or away from it when $\alpha > 0$

That is, we get **spiral sinks or sources**

Circles and Spiral Sinks and Sources

- We depict circles (left) and spiral sinks and sources (right) for planar systems in canonical form

Repeated Real Eigenvalue



From Hirsch et al., *Differential equations dynamical systems and an introduction to chaos*.

- We get a single repeated eigenvalue λ when we have

$$A = \begin{pmatrix} \lambda & 0 \\ 0 & \lambda \end{pmatrix} \quad \text{or} \quad A = \begin{pmatrix} \lambda & 1 \\ 0 & \lambda \end{pmatrix}$$

- In the first case the solutions are $X(t) = e^{\lambda t}V$ for any $V = X(0)$; thus the trajectories are straight lines through $(0, 0)$ that either tend to 0 when $\lambda < 0$ or to ∞
- The solutions in the second case are obtained by the method of **undetermined coefficients**: they are assumed of the form $x(t) = \alpha e^{\lambda t} + \mu t e^{\lambda t}$ for some α, μ
- Plugging this into the equation results in

$$X(t) = \alpha e^{\lambda t} \begin{pmatrix} 1 \\ 0 \end{pmatrix} + \mu e^{\lambda t} \begin{pmatrix} t \\ 1 \end{pmatrix}$$

- If $\lambda < 0$ the solutions $\rightarrow 0$ as $t \rightarrow \infty$; if $\lambda > 0$ they $\rightarrow \infty$
- In either case the solutions tend toward or away from $(0, 0)$ in a direction tangent to $(1, 0)$

Changing Coordinates

- Assume we want to solve $X' = AX, X(0) = x_0$ for a general matrix A
- We can find an invertible matrix T such that $M = TAT^{-1}$ is in canonical form
- Let Y be a solution of $Y' = MY$ with $Y(0) = y_0 = Tx_0$; setting $X = T^{-1}Y$ we obtain a solution of $X' = AX$ with $X(0) = T^{-1}y_0$
- Conversely, $Y = TX$ converts solutions of $X' = AX, X(0) = x_0$ into solutions of $Y' = TAT^{-1}Y$ with $Y(0) = y_0$
- The transformation T changes the initial coordinates X into the canonical form coordinates $Y = TX$
- Therefore the phase portraits for general planar systems $X' = AX$ can be derived from the phase portraits of canonical form system $Y' = MY$ by applying the T^{-1} coordinate change

- We thus obtain equilibrium points, sinks, sources, cycles or spirals that correspond to appropriate coordinate changes of the ones in canonical form

The Trace–Determinant Plane I

- It can be easily seen that the eigenvalue equation of a 2×2 matrix A is of the form

$$\lambda^2 - \operatorname{tr} A \lambda + \det A = \lambda^2 - \tau \lambda + \delta = 0$$

with solutions $\lambda_{\pm} = \frac{1}{2} (\tau \pm \sqrt{\tau^2 - 4\delta})$

- As a consequence we have
 - Complex conjugate eigenvalues when $\tau^2 < 4\delta$
 - Real different eigenvalues when $\tau^2 > 4\delta$
 - Real repeated eigenvalues when $\tau^2 = 4\delta$
- The parabola $\delta = \tau^2/4$ separates complex (above) from real (on or below) eigenvalues

The Trace–Determinant Plane II

- The real part of the complex eigenvalues above is $\tau/2$ and, therefore
 - We have a spiral sink if $\tau < 0$ and a spiral source when $\tau > 0$
 - We get a circle when $\tau = 0$
- Below the parabola we have a saddle when $\delta = \lambda_- \lambda_+ < 0$
- When $\delta > 0$, since $|\tau| > \sqrt{\tau^2 - 4\delta}$, we have $\operatorname{sign} \lambda_{\pm} = \operatorname{sign} \tau$; thus
 - We get a (real) source point when $\tau > 0$
 - We get a (real) sink point when $\tau < 0$
- One eigenvalue is 0 when $\delta = 0$ but $\tau \neq 0$ while both are 0 if $\delta = \tau = 0$

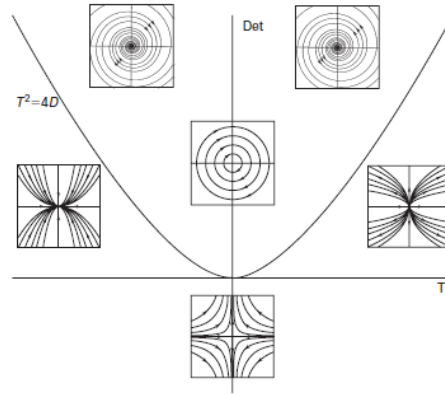
The Trace–Determinant Plane III

- The following plane diagram summarizes the preceding discussion

2.3 Nonlinear Dynamical Systems

Nonlinear Dynamical Systems

- A dynamical system (DS) is a procedure that describes the behavior in time of all points of a given space (Euclidean space, manifolds, ...)
- They are characterized by the **flow**, a function $\Phi_t : \mathbf{R}^d \rightarrow \mathbf{R}^d$ that takes x into $x_t = X(t) = \Phi_t(x)$
- We call them **discrete or continuous** depending on how we consider time change



From Hirsch et al., *Differential equations dynamical systems and an introduction to chaos*.

- Basic example: $\Phi_t(x)$ being the solution of a system of ordinary differential equations (ODE) $X' = F(X)$
- The behavior of general non linear DSs (NDS) may be quite complicated:
 - Most NDS are impossible to solve analytically
 - Some do not have solutions with a given initial value, some may have infinitely many ones
 - Solutions need not be defined for all time values t as they may tend to ∞ in finite time

Basic Results on ODEs

- **Existence and Uniqueness:** If F is C^1 , given t_0 and x_0 , there exists an $\epsilon > 0$ and a unique solution $X : (t_0 - \epsilon, t_0 + \epsilon) \rightarrow \mathbf{R}^d$ such that $X(t_0) = x_0$
 - Proved by the Picard iteration technique
 - We can show that we have a unique solution defined on a maximal time domain
 - However, the solution may not be defined for all t even for nice F
- **Continuous Dependence of Solutions:** If F is C^1 and $X(t)$ is a solution defined on $[t_0, t_1]$ with $X(t_0) = x_0$, then there is a neighborhood U of x_0 and a constant K such that if $y_0 \in U$, then there is a unique solution $Y(t)$ defined on $[t_0, t_1]$ with $Y(t_0) = y_0$ and for all $t \in [t_0, t_1]$

$$|Y(t) - X(t)| \leq K|y_0 - x_0|e^{K(t-t_0)}$$

- In particular the flow $\Phi_t(x)$ is continuous in X

- **Continuous Dependence on Parameters:** If $X' = F(X, a)$ and F is C^1 on a and x , the flow $\Phi_t(X, a)$ depends continuously on a

Phenomena on Nonlinear DS

- This is almost as far as the general theory goes: many more tools have been developed but are often applicable only on concrete systems ...
- Moreover new issues and non standard behavior appear: **bifurcations, strange attractor, chaotic systems**, ...
- Chaos (Lorenz): *When the present determines the future, but the approximate present does not approximately determine the future*
- The Lorenz's system opened the way to the consideration of these phenomena

Lorenz's System I

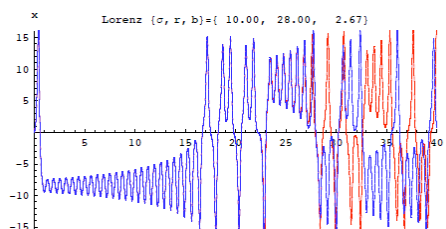
- First goal: a simple approximation to atmospheric flow that models as a two-dimensional fluid cell heated from below and cooled from above
- Further simplified to three independent variables: the rate of convectivity (x ; **convection**: the process of heat transfer by a moving fluid), and the horizontal and vertical temperature variation (y and z , respectively)
- Equations: for parameters σ, b, r

$$\dot{x} = \sigma(y - x); \dot{y} = r x - y - x z; \dot{z} = x y - b z$$

- The asymptotic behavior is relatively simple in some cases
 - $r < 1$: all solutions of the Lorenz system tend to the equilibrium point at the origin or
 - $1 < r < r^* = \sigma \left(\frac{\sigma+b+3}{\sigma-b-1} \right)$: the two non-zero equilibrium points Q_{\pm} , i.e., the solutions of $F(Q) = 0$, are sinks

Lorenz's System II

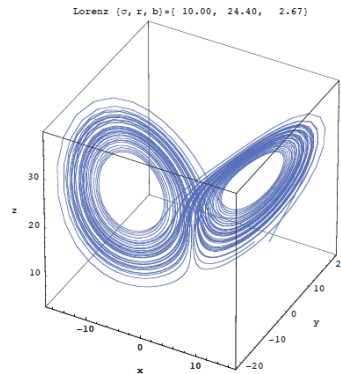
- Lorenz's significant parameters: $\sigma = 10$, $b = 8/3$, $r = 28$
- While being a deterministic system, it is very sensible to very small changes in initial conditions



- Butterfly effect: the flap of a butterfly's wing in Brazil can result in a tornado in Texas

Lorenz's Attractor

- All non-equilibrium solutions tend eventually to the so-called **Lorenz attractor**, roughly speaking an invariant set that “attracts” all nearby solutions



Discrete Dynamical Systems

- The theory of continuous DS focuses on the asymptotic behavior of solutions, assuming of course the system to be known
- If we are interested in (practical) prediction purposes we turn our attention to **discrete** DS (DDS)
- A Discrete Dynamical System is a pair (\mathcal{X}, T) made up of the **state space** \mathcal{X} (i.e., the set of all possible system states, that we assume bounded) and the map $T : \mathcal{X} \rightarrow \mathcal{X}$
- Starting at an $x_0 \in \mathcal{X}$ we get a **trajectory** or **orbit** $\{x_0, T(x_0), T^2(x_0), \dots\}$ of the system
- A way to catch the behaviour of a DDS is to study the asymptotic behavior of orbits
- Long-term system properties are described in terms of **attractors**

Attractors of DDSs

- As for planar systems, the simplest cases are those of attracting points or cycles, but much more complicated attractors are possible
- In broad terms, we say that a compact set A is an **attractor** of a DDS with fundamental neighborhood U if
 - **Invariance**: for all $x \in A$ and all n , $T^n(x) \in A$
 - **Attractivity**: there is an open subset V s.t. $A \subset V$ and if $x \in V$, $T^n(x) \in V$ for all n and $\bigcap_n T^n(V) = A$
 - **Transitivity**: given any points $y_1, y_2 \in A$ and open neighborhoods U_j of y_j in U , there is a solution curve starting at U_1 and passing through U_2

- When we talk about evolution on the attractor, we actually mean in a neighborhood of the attractor

DS Reconstruction I

- In practice the dynamical system itself is rarely known and its study has to be done from a single orbit
- Moreover, instead of an orbit usually the most we can get is a time series of **measurements**

$$Y = \{y_0, y_1, y_2, \dots\} = \{f(x_0), f(T(x_0)), f(T^2(x_0)), \dots\}$$

derived from a **read out map** $f : \mathcal{X} \rightarrow \mathbf{R}$

- In fact we often want a model $g : \mathbf{R}^k \rightarrow \mathbf{R}$ that helps us to predict the behavior of Y
- Q: Can we get it?

DS Reconstruction II

- At first sight we would need to know X to do any reconstruction
- So the first question could be:

Can we reconstruct the internal state of the system from such a TS?

- But getting X is hopeless; we may at most answer another question:

Can we get a somewhat equivalent representation of the internal state X from the TS?

- Tool: **reconstruction maps over time delays**
- For a fixed k define

$$R_k(x) = (f(x), f(T(x)), \dots, f(T^{k-1}(x)))$$

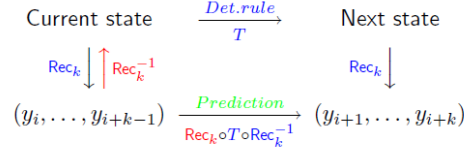
- Then $R_k(x_i) = (y_i, \dots, y_{i+k-1})$

Takens Theorem

- Assume \mathcal{X} is bounded and set $\mathcal{T} \times \mathcal{F}$ be the Cartesian product of the spaces of C^1 mappings T and C^1 readouts f ; then

There is an open dense subset $U \subset \mathcal{T} \times \mathcal{F}$ such that if $(T, f) \in U$ and $k > 2 \dim(\mathcal{X})$, the reconstruction map R_k is a C^1 embedding of \mathcal{T} in \mathbf{R}^k with a C^1 inverse

- The density of U implies that such an embedding exists “very near” any (T, f)
- Moreover, **the embedding preserves the structural properties of T** : the image $R_k(A)$ of an attractor A is an attractor (embedded) in \mathbf{R}^k and the observed orbit has the “same properties” of the underlying one
- More importantly, we have a path to predict the next state of the time series



S. Laur, Time Series of Deterministic Dynamic Systems, 2004

From Takens Theorem to Predictions

- We have the following diagram
- Setting $G = R_k^{-1} \circ T \circ R_k$, we have

$$(y_{i+1}, \dots, y_{i+k-1}, y_{i+k}) = G(y_i, \dots, y_{i+k-1}),$$

i.e., there is a function $g = G_1$ s.t. $y_{t+1} = g(y_t, \dots, y_{t-k+1})$ for all t

Time Series Prediction

- To exploit the preceding we need
 - A way to estimate an appropriate k
 - A way to estimate the function g
- The **correlation dimension** $cdim(A)$ of the attractor can be used to estimate an adequate k_0 : since $cdim(A) = cdim(R_k(A))$, we may look for a k_0 after which $cdim(R_k(A))$ stabilizes
 - Often this is easier said than done!!
- In any case, we get back to non-linear regression problems and ...
- We may look to say, MLPs (o SVR) models to approximate the non-linear AR model $y_{i+k} = g(y_i, \dots, y_{i+k-1})$

Back to TS Prediction by ML

- Predicting temporal information coming from either a time series or a dynamical system ends up in building proper models over time delays
 - Quite often we can/have to add exogenous information that can improve our predictions
- We thus fall in a natural way into possibly non-linear regression models that we may try to build using ML models

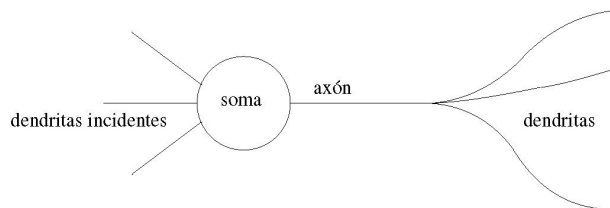
- The temporal structure should be preserved for instance when choosing train/test splits
- But this structure is often no longer taken into account after that
- ML models are usually built parameterizing the desired model as $f(x, w)$, defining a loss $L(w|S)$ over a sample S and minimizing L iteratively
- Handling temporal information comes thus back when actually training models
 - Because of sample patterns appearing sequentially
 - Or just in the iterative way model building proceeds
- We turn now to these issues

3 Machine Learning Basics

3.1 Rosenblatt's Perceptrons

Basic Neural Models

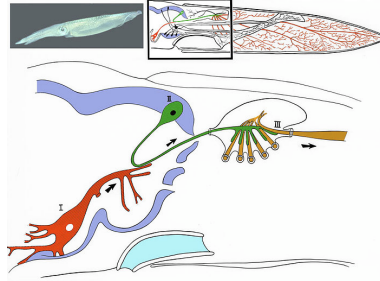
- Basic model: Ramón y Cajal's neuron (1900)



- Basic behavior: the neuron either fires or stays at rest depending basically on its inputs
- The brain has about 10^{11} neurons with each one having about 7,000 connections, often recurrent

Hodgkin–Huxley

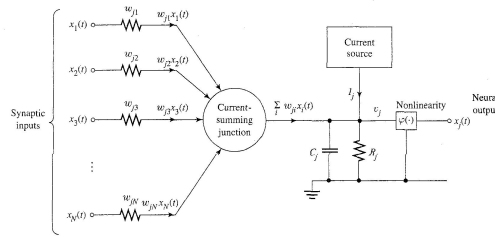
- They developed (circa 1935) the first model to describe the generation and propagation of electrical **action potentials** in neurons



From Wikipedia's [Squid Giant Synapse](#)

Electronic Neuron

- Electronic version: McCulloch–Pitts (1940)



- Since $I = \frac{V}{R} = wV$, with w the conductance, the McC–P neuron output is

$$H \left(\sum_{j=1}^d w_j V_j + I \right) = V$$

with the Heaviside function H ensuring a 0–1 output

- The **perceptron** is a mathematical formulation of the McC–P neuron where **the conductances are to be learned**

Rosenblatt's Perceptron

- Given a sample $S = \{(x^p, y^p)\}$ with $y^p = \pm 1$, Rosenblatt's Perceptrons (PCPs) are linear machines $w \cdot x$ such that

$$\begin{aligned} w \cdot x^p &> 0 & \text{if } y^p &= 1 \\ w \cdot x^p &< 0 & \text{if } y^p &= -1 \end{aligned}$$

- This can be seen as a **homogeneous** classification problem

- In more compact form we want for all p

$$y^p \cdot w \cdot x^p > 0$$

- If such a **separating** w exists, it can be computed in many ways
- Rosenblatt's goal was to **learn** w , i.e., to arrive at a separating w by repeatedly examining the (x^p, y^p) and adjusting w if necessary

Rosenblatt's Delta Rule

- The **Delta Rule** algorithm

```

Start with  $w = 0$ 
While stopping condition not met:
  Get a new pattern  $(x^p, y^p) = (x^{p(t)}, y^{p(t)})$ 
  if  $y^p w \cdot x^p \leq 0$  then:
     $w = w + y^p x^p$ 

```

- Writing w for the new vector and w' for the previous one, notice that

$$y^p \cdot w \cdot x^p = y^p \cdot w' \cdot x^p + \|x^p\|^2 > y^p \cdot w' \cdot x^p$$

Novikov's Theorem

- It states that if the sample S is linearly separable, the Delta rule yields a separating w in a finite number of steps
- More precisely, if for some separating hyperplane w with $\|w\| = 1$ we have $\min_p y^p w \cdot x^p = \gamma > 0$, then

a separating w' can be found after at most $T = R^2/\gamma^2$ wrong classifications, where $R = \max_p \|x^p\|$

- Notice that γ is the **margin** of the w hyperplane. Thus, if

$$\gamma^* = \max_{\|w\|=1} m(w, S) = \max_{\|w\|=1} \min_p y^p w \cdot x^p$$

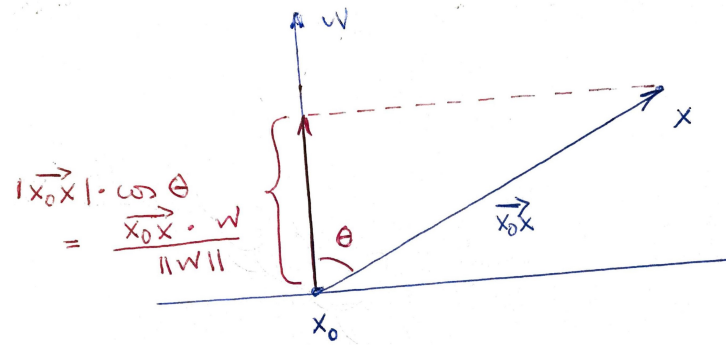
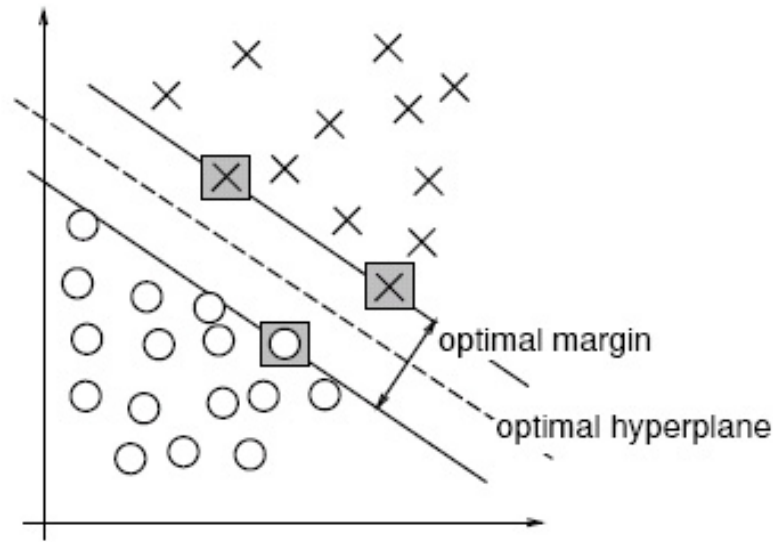
is the **maximum margin**, we will need at most $R^2/(\gamma^*)^2$ iterations to train a Perceptron

- The maximum margin hyperplane gives the best (smallest) Novikov bound
- And problems with smaller margins require more iterations

Margins and Generalization

- Intuitively, when the margin is large, the problem is easier

Distance to a Line



- Recall basic analytic geometry
- This extends to the multidimensional case: if $\|w\| = 1$ and $b = 0$, the distance of x to the hyperplane defined by w is $|w \cdot x| = yw \cdot x$

Proof Sketch

- Assume x^t is the t -th pattern such that $y^t w^{t-1} \cdot x^t \leq 0$
- Then $\|w^t\|^2 = \|y^t x^t + w^{t-1}\|^2 \leq \|x^t\|^2 + \|w^{t-1}\|^2$ and, thus,

$$\|w^t\|^2 \leq \|x^t\|^2 + \dots + \|x^1\|^2 + \|w^0\|^2 \leq tR^2$$

if $w^0 = 0$ and $\|x^p\| \leq R$ for all p

- Also, if w' is a 1-norm separating hyperplane i.e., $\min_p y^p w' \cdot x^p = \gamma > 0$ for all p , we have

$$w^t \cdot w' = (y^t x^t + w^{t-1}) \cdot w' \geq \gamma + w^{t-1} \cdot w' \geq \dots \geq t\gamma + w^0 \cdot w'$$

- Putting both together we have for all t for which x^t is erroneous

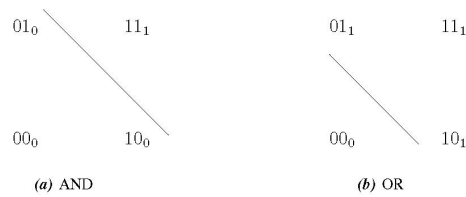
$$t\gamma \leq w^t \cdot w' \leq \|w^t\| \leq \sqrt{t}R$$

which implies $t \leq R^2/\gamma^2$

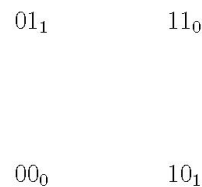
- Thus, the Delta Rule can stop after at most R^2/γ^2 iterations

Problems with Perceptrons

- Observation 1: A PCP can learn (obviously) only linearly separable problems; for instance, it can learn the AND and OR predicates



- But a PCP cannot learn the XOR predicate



Dichotomies

- Observation 2: for PCPs to be useful, linearly separable problems must be frequent
- Q: how frequent are they?
- A dichotomy for $S = \{x^1, x^2, \dots, x^N\}$ is any separation of S in two classes
- It corresponds to any assignment of the ± 1 values to the x^p
- The total number of dichotomies is 2^N

- Thus, the total number of 2-class problems over S is 2^N

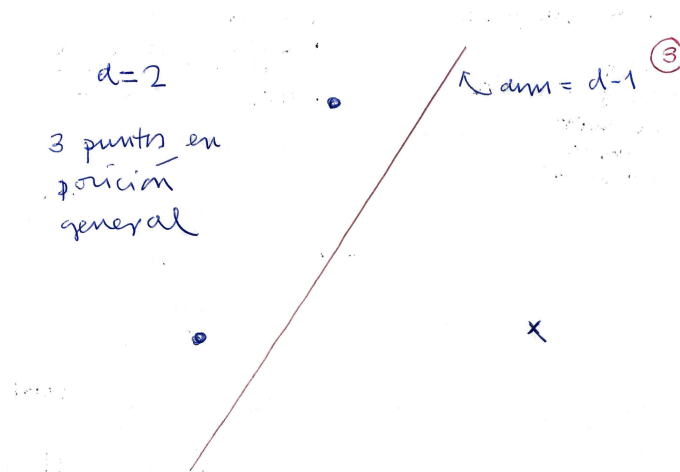
Cover's Theorem

- We have to compare the total number of dichotomies with the number of dichotomies that are **linearly separable**
- The points in a sample S are said to be in **general position** if there are not $d+1$ patterns in a $d-1$ -dimensional hyperplane
- **Theorem** If S is in general position, the number $L(N, d)$ of linearly separable dichotomies is

$$L(N, d) = \begin{cases} 2^N & \text{si } N \leq d+1 \\ 2 \sum_{i=0}^d \binom{N-1}{i} & \text{si } N \geq d+1 \end{cases}$$

Points in General Position

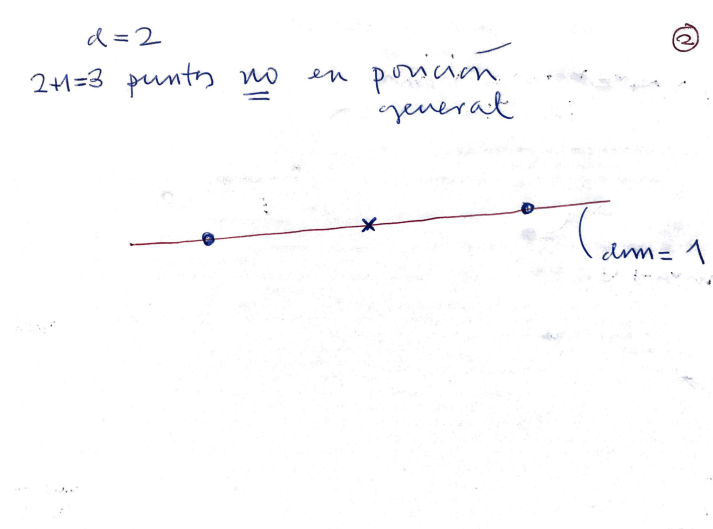
- Consider $d = 2$, $3 = d+1$ points and a $1 = d-1$ -dimensional hyperplane



Points Not in General Position

- Consider now $d = 2$ and $3 = d+1$ points **not** on a $1 = d-1$ -dimensional hyperplane (i.e., a line)

Thus ...



- Notice that for d fixed,

$$\frac{L(N, d)}{2^N} \rightarrow 0$$

as $N \rightarrow \infty$

- In practice we can expect $N \gg d$ and the fraction of separable dichotomies will be very small
- Thus, linear PCPs will not be useful
- But a one hidden layer PCP can solve XOR and, in fact, separate any convex region
- And a two hidden layers PCP can separate any polyhedral region and hence solve any classification problem
- The same is essentially true for regression problems
- But: **no algorithm is known to learn these 2-hidden layer PCPs**

Why Not Try to Minimize Some Loss?

- Rosenblatt's Perceptrons are natural **online** machines:
 - Patterns appear sequentially and each may change the current weights
- We can also define a perceptron loss over a given sample as

$$L(w|S) = - \sum_{\{p: y^p w \cdot x^p < 0\}} y^p w \cdot x^p$$

- The local error would thus be $-y^p w \cdot x^p$ when $y^p w \cdot x^p < 0$ and 0 otherwise

- Since $\nabla_w(-y^p w \cdot x^p) = -y^p x^p$, the Delta Rule can be seen as a kind of local gradient descent on the loss $L(w|S)$:

$$w^t = w^{t-1} + y^{p(t)} x^{p(t)} = w^{t-1} - \nabla_w \left(-y^{p(t)} w \cdot x^{p(t)} \right)$$

- However $L(w|S)$ is not differentiable and it is not clear what to make of $\nabla_w L(w|S)$...

What Can We Do?

- First option: work with linear models but somehow ensure that $d \gg N$
 - Transform the original d -dimensional features x in new D -dimensional ones such that $D \gg d$
 - We overcome then that, in practice, we usually have $N \gg d$
 - This is the goal of kernel-based Support Vector Machines
- Second option: build trainable PCPs replacing the Heaviside function
 - Work with differentiable PCP transfer function
 - Transform PCP training into a differentiable optimization problem
 - This is what we will do next
- Before doing so, note that **Rosenblatt's PCPs can be seen as the first Machine Learning model**
- And modern ML started around 1985 along the PCP's ideas

3.2 Machine Learning Modeling Basics

What Is Machine Learning (ML)?

- Lofty definition: make machines learn!!!
 - Have to make “machines” and “learn” more precise
- The machines of ML: mathematical input-output processes that lend themselves to some form of (numerical) parameterization
- The learning process: adjust the machine's parameters until a goal is reached
- New thing: “goal”?
 - At first sight, get something done
 - Ultimately, to minimize some error measure
- Summing things up: a ML process tries to find a concrete mathematical/algorithmic **input-output parameterized transformation that minimizes an error measure** by iteratively **adjusting the transformation's parameters**

Where Lies ML?

- In the middle of a possibly long process chain
- Before ML starts we must
 - Go from **raw to organized** data: accesing, gathering, cleaning, formatting, ...
 - Go from **organized to** (potentially) **informative** data: extracting basic and derived features
- After ML finishes we must perform
 - Outcome **evaluation**: how good/actionable it is
 - Outcome **exploitation**: collect, organize, act
 - **Individual model maintenance**: monitor performance, tune hyper-parameters
 - **Modeling life cycle maintenance**: discard old models, introduce new ones and **communicate** our work/results

Supervised/Unsupervised Models

- ML model types: **supervised, unsupervised**
- Supervised models:
 - Targets y^p are known and the model tries to predict or estimate them
 - These known targets guide, or **supervise**, model building
 - Main emphasis here
- Unsupervised models:
 - There are no predetermined or supervising outputs
 - But nevertheless the model is supposed to learn relations or find structure in the data
 - Often as a first step towards a supervised model
- Semisupervised models lie in between: some patterns have targets, some don't

Regression and Classification

- Problems (usually) to be solved by ML models: regression, classification
- Patterns come in pairs (x, y)
 - x : inputs, predictors, features, independent variables
 - y : target, response, dependent variable; numerical in regression, class labels in classification
- **Regression**: the desired output y is **regressed** into the inputs x to derive a model $\hat{y} = f(x)$
 - We want $y \simeq \hat{y}$ so having $y - \hat{y}$ “small” is the natural goal
- **Classification**: inputs are derived from several classes C_1, \dots, C_K , to which labels ℓ_k are assigned

- The model now assigns a label $\ell(x)$ to an input x
- If x is derived from C_k we want to have $\ell(x) = \ell_k$
- Here having $\ell(x) - \ell_k$ “small” may not make sense

The Boston Housing Problem

- This is a first “toy” problem
- We want to estimate the median of house values over an area from some information about it which we believe relevant
- Features x : several real estate-related variables of Boston areas
 - CRIM: per capita crime rate by town
 - RM: average number of rooms per dwelling
 - NOX: nitric oxides concentration (parts per 10 million)
 - AGE: proportion of owner-occupied units built prior to 1940
 - LSTAT: % lower status of the population
 - ...
- Target y : MEDV, median value of owner-occupied homes in \$1,000's

3.3 Regression Basics

Model Parameterization

- Usually individual models are selected through (ideally optimal) **parameter sets**
 - The parameters (weights) $w \in R^M$ select a concrete f in a model family \mathcal{F}
- **Parametric** models have a fixed functional form $f(x) = f(x; W)$
 - Simplest example: **linear regression**, where x has dimension d , $M = d + 1$ and $W = (w_0, w)$

$$f(x; w_0, w) = w_0 + \sum_{j=1}^d w_j x_j = w_0 + w \cdot x$$

- **Semi-parametric** models: also use weights but without a predefined functional form
 - MLPs but also RF or GBR
- **Non parametric** models do not use weights nor follow any broad functional form; Nearest Neighbor models

Issues in Model Building

- There are some initial questions when working with models from a given family \mathcal{F} :
 - Which assumptions do they make?

- How do they work on the input features?
- How we do build them?
- In turn, these questions lead to another two:
 - How do we select the best model from the given family for the problem at hand?
 - How do we control the model building procedure?
- All of them address fundamental issues that require a **moderately deep** understanding of what is going on under the model's hood
- This understanding is usually framed in **mathematical language**

How to Build Regression Models

- In general we have a sample $S = \{x^p, y^p\}$, $1 \leq p \leq N$, with x^p the **features** and y^p the **targets**
- We want to build a model $\hat{y} = f(x)$ so that $\hat{y}^p = f(x^p) \simeq y^p$;
 - I.e., we want to **regress** y to the $f(x)$
- The concrete f is chosen within a certain family \mathcal{F}
 - Examples here: linear regression, multilayer perceptrons (MLPs), SVMs
 - And also: Random Forests (RF), Gradient Boosting (GB), nearest neighbor (NN)
- Natural option to ensure $f(x^p) \simeq y^p$: choose f to minimize the sample **Mean Square Error (MSE)**

$$\hat{e}(f) = \hat{e}_S(f) = \frac{1}{2N} \sum_{p=1}^N (y^p - f(x^p))^2$$

- Thus, the model we select is $\hat{f} = \hat{f}_S = \arg \min_{f \in \mathcal{F}} \hat{e}_S(f)$

Model Estimation as Error Minimization

- For a parametric or semiparametric $f(x; W)$ we can write $\hat{e}_S(f) = \hat{e}_S(f(\cdot; W)) = \hat{e}_S(W)$
- The problem to solve becomes

$$\hat{W}^* = \hat{W}_S^* = \arg \min_W \hat{e}_S(W), \quad \text{i.e., } \hat{e}_S(\hat{W}^*) \leq \hat{e}_S(W) \quad \forall W$$

- In linear regression the sample error is

$$\hat{e}(w_0, w) = \frac{1}{2N} \sum_p (y^p - w_0 - w \cdot x^p)^2$$

i.e., the **sample** error, with a corresponding **population** error

$$e(w_0, w) = \frac{1}{2} E_{x,y}[(y - f(x))^2] = \frac{1}{2} E[(y - w_0 - w \cdot x)^2 p(x, y) dx dy]$$

- Linear regression reduces to **minimize the quadratic form** $\widehat{e}_S(W)$

Regression Assumptions

- **Key assumption:** x and y are related as $y = \phi(x) + n$ where
 - $\phi(x)$ is the **true** underlying function
 - n is **additive noise** with 0 mean and finite variance σ_N^2
- Our sample is just a particular instance of a deeper **sample generation process**
- Thus x, n are produced by **random variables** X, N
 - And so is y , given by $Y = \phi(X) + N$
- Moreover, X and N are **independent distributions** with densities $q(x), \nu(n)$
- Thus, X and Y (or X and N) have a joint density

$$p(x, y) = p(x, \phi(x) + n) = q(x) \nu(n) = q(x) \nu(y - \phi(x))$$

MSE Decomposition

- We can decompose the MSE error of any model f as

$$\begin{aligned} 2\text{mse}(f) &= E_{x,y}[(y - f(x))^2] = \int (n + \phi(x) - f(x))^2 q(x) \nu(n) dx dn \\ &= \int (n^2 + 2n(\phi(x) - f(x)) + (\phi(x) - f(x))^2) q(x) \nu(n) dx dn \\ &= \int n^2 \nu(n) dn + \int (\phi(x) - f(x))^2 q(x) dx + \\ &\quad 2 \left(\int n \nu(n) dn \right) \left(\int (\phi(x) - f(x)) q(x) dx \right) \\ &= \sigma_N^2 + E_x[(\phi(x) - f(x))^2] \end{aligned}$$

- Thus **for any model we have $\text{mse}(f) \geq \sigma_N^2$ always**
- And we should focus on achieving on $f \simeq \phi$ (which we don't know!!)

The Best Regression Model

- It is easy to see that the best f is simply $f(x) = E_y[y|x]$, for

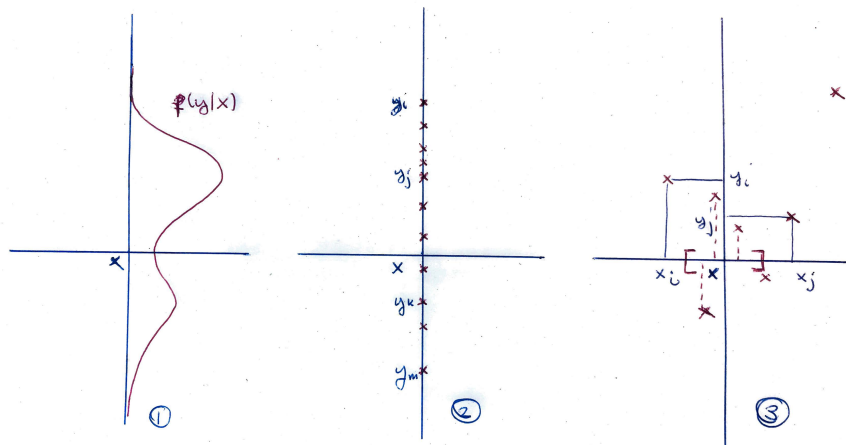
$$E_y[y|x] = E_n[\phi(x) + n] = \int (\phi(x) + n) \nu(n) dn = \phi(x)$$

- Have we finished? In theory yes; in practice, not at all!!!
 - We do not know ν and, thus, cannot compute the required integral
 - If we would have several M values y^j for any x , we could try $\widehat{\phi}(x) = \frac{1}{M} \sum_1^M y^j$

- But this doesn't happen either
- Now we have two options:
 - Try to stretch the $E[y|x]$ approach, for instance, by **k -NN Regression**
 - Forget about it and get back to get models f such that $f \simeq \phi$

From The Best Regressor to k -NN

- The left hand side shows the ideal situation but the right one is what we should expect



k -NN Regression

- We can try to use the y^p values of several x^p close to a new x
- We fix k neighbors x^{p_1}, \dots, x^{p_k} of x and estimate $\hat{y} = \hat{y}(x)$ as

$$\hat{y}(x) = \frac{1}{k} \sum_{j=1}^k y^{p_j}$$

- $\hat{y}(x) = \hat{Y}_k^{NN}(x)$ is the **k -Nearest Neighbor (NN)** regressor

- This can be refined to weighted versions, such as

$$\hat{y}(x) = \frac{1}{C_k(x)} \sum_{j=1}^k \frac{1}{\|x^{p_j} - x\|^2} y^{p_j}$$

with $C_k(x) = \sum_{j=1}^k \frac{1}{\|x^{p_j} - x\|^2}$ a normalizing constant

- But we need that close predictors give predictions that are also close, **and** that there are enough of them close by
 - This is **very unlikely**

The Curse of Dimensionality

- Even for low dimensions and large samples, **the sample space is essentially empty**
- Assume we have 1,000 d -dimensional x patterns whose features have values between 1 and 10
 - In dimension $d = 1$ there are 100 patterns per unit length
 - But when $d = 3$ we have just 1 pattern per volume unit
 - And if $d = 6$ we have just 1 pattern per 1,000 units of volume
 - And in dimension 10 (not a big one nowadays) we have just ... !!!
- Thus, for most problems, **there never will be enough close points**
- As a consequence, to get k observations we may go too far away from x and the average will not be meaningful
- Therefore, unless we deal with violently non-linear problems, a simple linear model may be better than k -NN regression for moderate dimensions

Linear Models

- Assuming $x \in R^d$, the basic linear model is

$$f(x) = w_0 + \sum_1^d w_i x_i = w_0 + w \cdot x$$

- w_0 complicates notation; to drop it we center x and y so that $E[x_i] = E[y] = 0$; then $w_0 = 0$
- Then we are left with the simpler **homogeneous** model $f(x) = w \cdot x$
- In practice we will always **normalize** x , for instance to have 0 mean and 1 standard deviation (std) on each feature
 - But not y if we may help it (or it is easy to reverse this)
- But: how do we find w ?

1-dimensional Linear Regression (LR)

- Assume that features X and target Y are **centered**, i.e., have 0 means
- For 1-dimensional patterns x the LR model then becomes $f(x) = w x$
- And the error is then the function

$$\begin{aligned}\widehat{e}(w) &= \frac{1}{2N} \sum_{p=1}^N (w x^p - y^p)^2 = \frac{1}{2N} \sum_p (w^2 (x^p)^2 - 2x^p y^p w + (y^p)^2) \\ &= w^2 \left(\frac{1}{2N} \sum_p (x^p)^2 \right) - w \left(\frac{1}{N} \sum_p x^p y^p \right) + \frac{1}{2N} \sum_p (y^p)^2\end{aligned}$$

- Thus, $\widehat{e}(w) = aw^2 + bw + c$ with $a > 0$ and it has obviously a minimum w^*
- To find it we just solve $\widehat{e}'(w) = 0$

Solving $\widehat{e}'(w) = 0$

- We first compute $\widehat{e}'(w)$, for which we have

$$\widehat{e}'(w) = w \left(\frac{1}{N} \sum_p (x^p)^2 \right) - \frac{1}{N} \sum_p x^p y^p$$

- The optimal w^* solves $\widehat{e}'(w) = 0$ and is given by

$$w^* = \frac{\frac{1}{N} \sum_p x^p y^p}{\frac{1}{N} \sum_p (x^p)^2} = \frac{\frac{1}{N} X^t Y}{\frac{1}{N} X^t X} = \frac{\text{covar}(x, y)}{\text{var}(x)}$$

where X and Y denote the N dimensional vectors $(x^1, \dots, x^N)^t, (y^1, \dots, y^N)^t$

General Linear Regression

- Assume again that X and Y are centered
- The LR model becomes now $f(x) = \sum_1^d w_i x_i = w \cdot x$
- If Y is the $N \times 1$ **target** vector and we organize the sample S in a $N \times d$ **data matrix** X , the sample mse is given by

$$\begin{aligned}\widehat{e}(w) &= \frac{1}{2N} \sum_p (w \cdot x^p - y^p)^2 = \frac{1}{2N} (Xw - Y)^t (Xw - Y) \\ &= \frac{1}{2N} (w^t X^t X w - 2w^t X^t Y + Y^t Y)\end{aligned}$$

- Now we have to solve $\nabla \widehat{e}(w) = 0$, i.e., $\frac{\partial \widehat{e}}{\partial w_i}(w) = 0$

- It is easy to see that

$$\nabla \hat{e}(w) = \frac{1}{N} X^t X w - \frac{1}{N} X^t Y = \hat{R} w - \hat{b}$$

Solving the Linear Equations

- The optimal \hat{w}^* must verify $\nabla \hat{e}(\hat{w}) = \hat{R} \hat{w} - \hat{b} = 0$, where

$$\hat{R} = \frac{1}{N} X^t X, \quad \hat{b} = \frac{1}{N} X^t Y$$

- Over the original, non-centered data matrix we have

$$\hat{R} = \frac{1}{N} (X - \bar{X})^t (X - \bar{X});$$

i.e., \hat{R} is the **sample covariance matrix**

- If \hat{R} is invertible, we just solve the linear system $\hat{R} \hat{w} - \hat{b} = 0$
- And obtain the sample-dependent optimal \hat{w}^* as

$$\hat{w}^* = \hat{R}^{-1} \hat{b} = (X^t X)^{-1} X^t Y = \text{covar}(X)^{-1} \text{covar}(X, Y)$$

- \hat{R} is oftent inverted through the **Singular Value Decomposition** (SVD) of the data matrix X

SVD

- The **Singular Value Decomposition** (SVD) of a $N \times d$ matrix X is $X = UDV^t$ where
 - U, V are orthonormal matrices with dimensions $N \times d$ and $d \times d$
 - D is a $d \times d$ diagonal matrix with diagonal elements $\delta_1 \geq \delta_2 \geq \dots$
 - We can use D to check the invertibility of \hat{R}
- Then $XX^t = UDV^t VDU^t = UD^2U^t$
- The columns of U and V are called the left and right singular vectors; the elements δ_i are the singular values
- The columns of U and V are unique up to a sign change
 - So different packages may give seemingly different U and V

Gradient Descent MSE Minimization

- Computing the covariance matrix has a $O(N \times d^2)$ cost and invert it has a $O(d^3)$ cost
 - For big data problems it may not possible to solve analytically the normal equation $\nabla \hat{e}(w) = 0$
- The simplest numerical alternative is **gradient descent**:

- Starting from some random w^0 , we iteratively compute

$$w^{k+1} = w^k - \rho_k \nabla \hat{e}(w^k) = w^k - \frac{\rho}{n_B} \left(\hat{X}_B^t \hat{X}_B w^k - \hat{X}_B^t Y \right)$$

over a **mini-batch** B with n_B samples

- Component wise: $w_i^{k+1} = w_i^k - \rho_k \frac{\partial \hat{e}}{\partial w_i}(w^k)$
- ρ_k is the **learning rate**
- If $w^k \rightarrow w^*$, then $\nabla \hat{e}(w^*) = 0$
 - Since our problems have obviously minima, this should be enough

Measuring Model Fit

- First option: **Root Square Error** $RSE = \sqrt{\frac{1}{N} \sum (y^p - \hat{y}^p)^2}$
- OK, but how good is this? We must always have a **base model** to benchmark our results
- Simplest “model”: a constant w_0 , which yields the mean $\bar{y} = \frac{1}{N} \sum_1^N y^p$, with square error

$$\frac{1}{N} \sum (y^p - \bar{y})^2 = \text{Var}(y)$$

- We can compare our model against this base model by computing

$$\frac{\sum (y^p - \hat{y}^p)^2}{\sum (y^p - \bar{y})^2} = \frac{RSE^2}{\text{Var}(y)}$$

- The widely used R^2 coefficient is simply $R^2 = 1 - \frac{RSE}{\text{Var}(y)}$

Regularization

- Our regression solution $\hat{w}^* = (X^t X)^{-1} X^t Y$ won't work if $X^t X$ is not invertible
 - For instance, when some features are correlated
- We could fix this working instead with $X^t X + \alpha I$ for some $\alpha > 0$
 - It is then always positive definite and we can thus invert it
- To make this practical, note that $\hat{w}^* = (X^t X + \alpha I)^{-1} X^t Y$ minimizes

$$e_R(w) = \frac{1}{2N} \sum_p (y^p - w \cdot x_p^p)^2 + \frac{\alpha}{2} \|w\|^2,$$

- This is the **Ridge Regression** problem
 - Our first example of **regularization**, a key technique in Machine Learning
 - **All ML models must be regularized in some way**
- Important issue: how to find the right choice for α ?

Takeaways on Linear Regression

1. We introduced **supervised** models
2. We have reviewed the essentials of the **linear regression model** (always the first thing to try)
3. We have considered model estimation as a problem on **error minimization**
4. We have seen how to build linear models **analytically and numerically**
5. We have seen how to **measure model fit**
6. We have introduced **regularization**

3.4 Bias, Variance and Cross Validation

Sample Bias and Variance

- All built models are **sample dependent**
- With several **independent** samples S_1, \dots, S_M , it is natural to use as our best final model the average of their associated $\hat{f}_{S_m}(x)$ models, i.e.,

$$\frac{1}{M} \sum_1^M \hat{f}_{S_m}(x) \simeq E_S[\hat{f}_S(x)] = \hat{f}_N(x)$$

– We take the expectation $E_S[\hat{f}_S(x)]$ over all samples S of size N

- $\hat{f}_N(x) = E_S[\hat{f}_S(x)]$ is our ideal **best model**
- The **variance** of the $\hat{f}_S(x)$ estimates is then

$$V_N(x) = E_S [(\hat{f}_S(x) - \hat{f}_N(x))^2]$$

Bias Versus Variance

- Given our regression model $y = \phi(x) + n$, our goal is to estimate ϕ
- Ideally we would like to have a model such that

$$\hat{f}_N(x) - \phi(x) \simeq 0,$$

i.e., a model with small **bias**

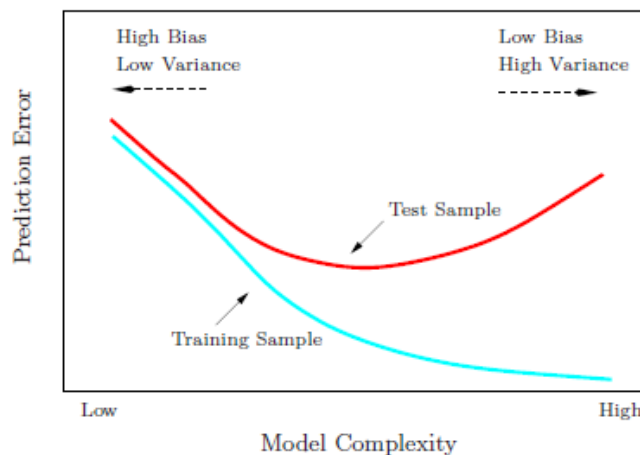
- This should be achievable if we have rich, highly flexible models
- Or with essentially no regularization (or both!)

- But we would also like to have a robust model building procedure which results in a small **variance** $V_N(x) \simeq 0$

- This should be achievable if models are simple with few parameters
- Or with more severe regularization if not
- Obviously both goals are contradictory to a large extent

The Bias–Variance Tradeoff

- There is thus a **tradeoff** between bias (low for complex models) and variance (low for simple models)



Taken from *Hastie et al.*, p. 38

Two Examples

- In k -NN regression the parameter that controls the tradeoff is just k
 - If $k = N$, the sample size, the N -NN estimator is just the mean: $Y_N^{NN} = \bar{y}$, with very small variance but large bias (it's an obviously bad model!!)
 - If $k = 1$, the 1-NN estimator will have smaller bias but a large variance: changing the sample is very likely to change the sample point nearest to x
- In Ridge regression the parameter that controls the tradeoff is the regularization penalty α
- If $\alpha \gg 1$, any non zero w implies a large regularization penalty
 - It is thus likely that $w \simeq 0$ and the Ridge model reduces again to the mean \bar{y} , with large bias and small variance
- But if $\alpha \simeq 0$, w can wander on the entire \mathbf{R}^d
 - The bias will be then smaller, but the weights w_S and $w_{S'}$ from different samples may be very different, particularly if the covariance is nearly singular

Evaluating Expected Performance

- It is obvious that before we start applying a model, we should have a reasonably accurate idea of its performance in practice
- I.e., we want to estimate the model's **generalization performance**
- Estimating the generalization performance **only over the sample S used for training results in misleading error values**
- The preceding suggests to have M independent subsamples S_m and then
 - To compute $\hat{f}_M(x) = \frac{1}{M} \sum_m \hat{f}_{S_m}(x) \simeq \hat{f}_N(x)$
 - To get the error estimate $\hat{e} = \frac{1}{N} \sum_p (y^p - \hat{f}_M(x^p))^2$ over a new, **unseen** sample $S' = \{(x^p, y^p)\}$
- But since usually we only have a single S , we “simulate” this by **Cross Validation (CV)** to get our first realistic generalization error estimates

Cross Validation

- In Cross Validation (CV) we
 - Randomly split the sample S in M subsets S_1, \dots, S_M
 - Work with M **folds**: pairs (S_m, S_m^c) , with

$$S_m^c = S - S_m = \cup_{i \neq m} S_i$$
 - Build M different models **using the S_m^c as training subsets**
 - Compute their errors e_m on the folds' **validation subsets S_m**
 - Use these errors' average as a first estimate of the true model performance
- CV can and **must be used** in any model building procedure
 - Most data science packages have tools to simplify this
- We will also use CV to find **optimal model hyper-parameters** such as α in Ridge Regression

Grid Hyper-parameter Selection

- Consider for Ridge regression a hyperparameter range $[\epsilon, A]$, with $0 \leq \epsilon < A$
 - $\alpha = \epsilon$: essentially no penalty, small bias and high variance
 - $\alpha = A$: large penalty, small variance but high bias
- Select an $L + 1$ point **grid** $\{\alpha_0 = \epsilon, \alpha_1, \dots, \alpha_L = A\}$
 - The α_j can be equi-spaced, log equi-spaced, random, ...
- At each α_ℓ

- Train M models on the S_m^c using the hyperparameter α_ℓ
- Average their test errors e_m on the S_m to get the error $e(\alpha_\ell)$ at α_ℓ
- And choose the final (hopefully) optimal hyperparameter α^* as

$$\alpha^* = \arg \min_{0 \leq \ell \leq L} e(\alpha_\ell)$$

- α^* gives the model with the **best expected generalization among all possible α choices**

Takeaways on Bias, Variance and CV

1. We have stressed that **any model estimation is sample-dependent** and that this has to be controlled
2. We have introduced the **bias** and **variance** as the two key components of any model error
3. We have discussed **bias-variance trade-off**
4. We have introduced **Cross Validation** here as a tool to estimate a **model's generalization performance**
5. We have also introduced **Cross Validation** as a tool to estimate a **model's hyperparameters**

3.5 Logistic Regression

Linear Regression for Classification?

- Building a regression model with targets given by some coding of class labels usually doesn't make sense
- However, for a binary 0–1 response, it can be shown that the $w_0 + w \cdot x$ obtained using linear regression is in fact an estimate of $P(1|x)$
 - We may thus fix a threshold δ_0 and decide 0 if $w_0 + w \cdot x < \delta_0$ and 1 otherwise
 - However, we may end up with probability estimates less than 0 or bigger than 1!!!
- Better idea: try to transform the linear output $w_0 + w \cdot x \in (-\infty, \infty)$ into a probability $P(1, x) \in (0, 1)$
- The sigmoid function $\frac{1}{1+e^{-z}}$, a smoothing of the Heaviside function, does just that

Logistic Regression (LR)

- We assume

$$P(1|x) = P(1|x; w_0, w) = \frac{1}{1 + e^{-(w_0 + w \cdot x)}}$$

- Then $0 \leq P(1|x) \leq 1$ for any x and we have

$$P(0|x) = 1 - P(1|x) = \frac{e^{-(w_0 + w \cdot x)}}{1 + e^{-(w_0 + w \cdot x)}} = \frac{1}{1 + e^{w_0 + w \cdot x}}$$

- Notice that if $w_0 + w \cdot x = 0$, $P(1|x) = P(0|x) = 0.5$
- The ratio $\frac{P(1|x)}{P(0|x)} = e^{w_0 + w \cdot x}$ is called the **odds** of x and its log the **log odds** or **logit**
- Thus, the basic assumption in LR is that the **logit is a linear function** $w_0 + w \cdot x$ of x
- We have the model $f(x; w)$; we need a **loss** function $L(w_0, w)$ to minimize for which we use the sample's **likelihood**

Estimating w_0^*, w^*

- Assume a single sample x, y and two possible model coefficients w_0, w and w'_0, w'
- Denoting by $p = P(y|x; w_0, w)$ and $p' = P(y|x; w'_0, w')$, it is clear that we should prefer w_0, w if $p > p'$ and w'_0, w' if not
 - In other words, we prefer the coefficients that give a **higher posterior probability** to the sample (x, y)
- For an independent sample $S = \{(x^p, y^p)\}$, its joint probability under a posterior model $p = P(y|x; w_0, w)$ is

$$P(Y|X; w_0, w) = \prod_{p=1}^N P(y^p|x^p; w_0, w)$$

- And, again, given two possible model coefficients w_0, w and w'_0, w' , we should prefer w_0, w iff

$$P(Y|X; w_0, w) > P(Y|X; w'_0, w')$$

Sample's Likelihood

- Therefore, we can estimate the optimal w_0^*, w^* as

$$w_0^*, w^* = \arg \max_{w_0, w} P(Y|X; w_0, w)$$

- By the independence assumption we have

$$\begin{aligned} P(Y|X; w_0, w) &= \left\{ \prod_{y^p=1} P(1|x^p) \right\} \left\{ \prod_{y^p=0} P(0|x^p) \right\} \\ &= \prod_{p=1}^N P(1|x^p)^{y^p} P(0|x^p)^{1-y^p} \end{aligned}$$

with the last equality follows from

- If $y^p = 1$, $P(1|x^p) = P(1|x^p)^{y^p} P(0|x^p)^{1-y^p}$, and
- If $y^p = 0$, $P(0|x^p) = P(0|x^p)^{1-y^p} P(1|x^p)^{y^p}$

Max Log–Likelihood Estimation

- The log-likelihood of w_0, w given S is then

$$\begin{aligned}
 \ell(w_0, w; S) &= \log P(Y|X; w_0, w) \\
 &= \sum_{p=1}^N \{y^p \log P(1|x^p) + (1 - y^p) \log P(0|x^p)\} \\
 &= \sum_p y^p \log \frac{P(1|x^p)}{P(0|x^p)} + \sum_p \log P(0|x^p) \\
 &= \sum_p y^p (w_0 + w \cdot x^p) - \sum_p \log(1 + e^{w_0 + w \cdot x^p})
 \end{aligned}$$

- We can thus estimate the optimal \hat{w}_0^*, \hat{w}^* as

$$\hat{w}_0^*, \hat{w}^* = \arg \min_{w_0, w} -\ell(w_0, w; S)$$

- Extra bonus: $-\ell$ is a **convex** differentiable function of (w_0, w) and, thus, it is enough to solve $\nabla \ell(w_0, w) = 0$

Newton–Raphson Solution

- However, $\nabla \ell(W) = \nabla \ell(w_0, w) = 0$ doesn't admit a closed form solution but only an iterative, numerical one
- We solve it by the **Newton–Raphson** iterative method (equivalent here to Newton's method for minimization)
- Starting from a random $W^0 = (w_0^0, w^0)$, Newton's iterations are

$$W^{k+1} = W^k - (\mathcal{H}_\ell(W^k))^{-1} \nabla \ell(W^k)$$

- $\mathcal{H}_\ell(W^k)$ denotes the Hessian of ℓ at W^k (which may or may not be invertible)
 - Everything is fine if the W^k are close enough to the optimum W^* but far away things may get tricky
- Just as before, we can add a regularization term $\frac{\alpha}{2} \|w\|^2$
- The iterations in Logistic Regression are again typical of many of the model building methods used in Machine Learning

Learning in ML

- The general approach to **learning** is usually the following:
 - A **model** $f(x; W)$ is chosen
 - Given a sample $S = \{(x^1, y^1), \dots, (x^N, y^N)\}$ and a loss function $\ell(y, \hat{y})$, we define a **sample dependent loss function**

$$L(W) = L(W|S) = \sum \ell(y^p, \hat{y}^p = f(x^p; W))$$

- $L(W)$ is often minimized from some W^0 by **iterations**

$$W^{k+1} = W^k - \rho_k G(W^k, S)$$

with ρ_k a **learning rate** and G some vectorial function

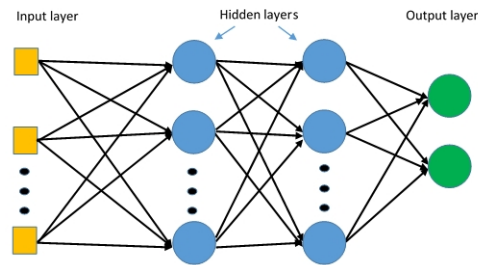
- When $G(W) = \nabla L(W)$ we have **gradient descent**
- When $G(W) = \mathcal{H}(W)^{-1} \nabla L(W)$ we obtain **Newton's method**
- In **batch learning** the entire sample S is used at each iteration
- **On-line** or **minibatch learning**: we use either a single patterns (x^p, y^p) or small sub-sample

4 Multilayer Perceptrons

4.1 Classical MLPs

MLP Architecture

- General layout:
 - An input layer (input)
 - One or several hidden layers
 - One output layer
- Feedforward connections only



- Example: [TensorFlow Playground](#)

MLP Connections

- No feedback or lateral connections
- Fully connected layers
- Linear unit connections and (usually) non linear activations inside each unit
 - Combined effect of sucesive layers: potentially highly non-linear transformation

- General processing: layered and feedforward
- In practice (1990s), one hidden layer and only sometimes two
- Later (around 2010): Deep Networks with “many” (from 3 to 10) layers
- Now: almost anything!

Unit Activation and Output

- The **activations** a_i^h of a unit in layer h receives the **outputs** from processing in the previous layer

$$a_i^h = \sum_{j=1}^{n_{h-1}} w_{ij}^h o_j^{h-1} + b_i^h,$$

- In matrix/vector form:

$$a^h = W^h o^{h-1} + b^h$$

- **Output** o_i^h of a unit: non linear processing of its activation $o_i^h = \varphi(a_i^h)$
- In vector form:

$$o^h = \varphi(a^h),$$

where φ is applied over each unit

Activation Functions

- Choices for f :
 - Heaviside (in the very first Rosenblatt’s Perceptrons): $\varphi(a) = 0$ if $a \leq 0$, $\varphi(a) = 1$ if $a > 0$
 - Identity/linear: $\varphi(a) = a$
 - Sigmoid:

$$\varphi(a) = \sigma(a) = \frac{1}{1 + e^{-a}}$$

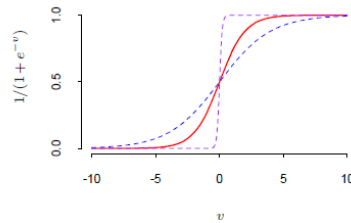
- Hyperbolic tangent:

$$\varphi(a) = \tanh(a) = \frac{e^a - e^{-a}}{e^a + e^{-a}}$$

- Rectified Linear Units (ReLUs): $\varphi(a) = r(a) = \max(0, a)$

Sigmoid and Hyperbolic Tangent

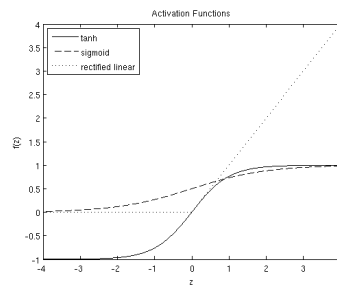
- Sigmoid and tanh: smooth version of Heaviside step function
- Classical choices:



- Hyperbolic tangent for hidden units
- Linear outputs for modelling (and sometimes) classification problems
- Sigmoid outputs for classification problems (as in logistic regression)

ReLU

- ReLU transfer function: $r(x) = \max(0, x)$



From [Stanford's UFLDL Tutorial](#)

- We have $r'(x)$ either 0 or 1 (hoping $x = 0$ never happens!!)
 - Many gradient elements will go to 0
 - Many units (neurons) will be “dead”, with a 0/constant activation no matter the input

The Simplest MLP I

- The Single Hidden Layer (SHL) MLP
 - D inputs (determined by the problem at hand)
 - One hidden layer with H units (number to be chosen) and tanh activation
 - One linear or sigmoid output (according to the problem at hand)
- Input-hidden processing: denoting inputs by x and the hidden unit output as o ,

$$o^h = \tanh \left(b_h^H + \sum_{j=1}^D W_{hj}^H x_j \right)$$

- In matrix/vector form: $o = \tanh (W^H x + b^H)$

The Simplest MLP II

- Hidden-output processing: since targets are 1-dimensional, we have for the outputs \hat{y}

$$\hat{y} = \sum_{h=0}^H w_h^O o_h + b^O,$$

- In vector form: $\hat{y} = w^O \cdot o + b^O$
- That is, a **linear model** on the last hidden layer outputs
- Global process:

$$\hat{y} = f(x; w^O, W^H, b^O, b^H) = b^O + \sum_h w_h^O \tanh \left(b_h^H + \sum_j W_{hj}^H x_j \right)$$

- Or in matrix/vector form

$$\hat{y} = f(x; w^O, W^H, b^O, b^H) = b^O + w^O \cdot \tanh (b^H + W^H x)$$

MLPs and Universal Approximation

- Recall that the regression goal is to get $f \simeq \phi$
- We say that $\mathcal{F} = \{f(x; \mathcal{W})\}$ is a **Universal Approximation Family** over a domain \mathcal{R} if

For any $\epsilon > 0$ and any reasonable ϕ , we can find an $f(x; \mathcal{W}_{\phi, \epsilon})$ s.t.

$$\int (\phi(x) - f(x; \mathcal{W}_{\phi, \epsilon}))^2 p(x) dx \leq \epsilon$$

- Notice that Universal Approximation is just what we need in regression
- In fact a **Single Hidden Layer MLP with enough hidden units is an effective universal approximator**
- But we have to be able to build them

MLP Error Function

- MSE is the standard error function for regression MLPs

$$\begin{aligned} e(\mathcal{W}) &= \frac{1}{2} E_{x,y} [(y - f(x; \mathcal{W}))^2] = E_{x,y} [e^\ell(x, y; \mathcal{W})] \\ &= \int e^\ell(x, y; \mathcal{W}) p(x, y) dx dy \end{aligned}$$

with $e^\ell(x, y; \mathcal{W})$ denotes the **local error**

$$e^\ell(x, y; \mathcal{W}) = \frac{1}{2} (y - \hat{y})^2 = \frac{1}{2} (y - f(x; \mathcal{W}))^2$$

MSE Gradient

- The general idea would be to obtain \mathcal{W}^* as a solution of $\nabla e(\mathcal{W}) = 0$, where we have

$$\begin{aligned}\nabla e(\mathcal{W}) &= E_{x,y} [\nabla_{\mathcal{W}} e^\ell(x, y; \mathcal{W})] \\ &= E_{x,y} [\nabla_{\mathcal{W}} f(x; \mathcal{W})(f(x; \mathcal{W}) - y)]\end{aligned}$$

for we have

$$\begin{aligned}\nabla_{\mathcal{W}} e^\ell(x, y; \mathcal{W}) &= -(y - f(x; \mathcal{W})) \nabla_{\mathcal{W}} f(x; \mathcal{W}) \\ &= \nabla_{\mathcal{W}} f(x; \mathcal{W})(f(x; \mathcal{W}) - y)\end{aligned}$$

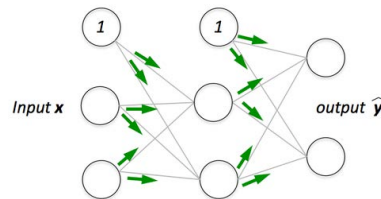
- We have therefore two tasks:
 - Compute ∇e
 - Exploit it to build MLPs
- We will exploit $\nabla e(\mathcal{W})$ through **optimization methods** after we compute it

SHL Forward Pass I

- We apply the preceding to a single hidden layer (SHL) MLP with
 - A single output unit and input-to-hidden weight matrix $W^H = (W_{hj}^H)$ and bias b^H vector and
 - A hidden-to-output weight vector $w^O = (w_1^O, \dots, w_H^O)$ and scalar bias b^O
- Recall that the forward pass can be computed as follows
 - $a = W^H x + b^H$, $o = \varphi(a)$,
 - Or unit-wise: $a_h = \sum W_{hi}^H x_i + b_i^H$, $o_h = \varphi(a_h)$
 - $y = w^O \cdot o + b^O = \sum_h w_h^O o_h + b^O$
- Straightforward to program

SHL Forward Pass II

- Graphically we have the following scheme:



From [Sebastian Raschka's A Visual Explanation of the Back Propagation Algorithm for Neural Networks](#), [KDNuggets](#)

- We turn next to the gradient computation
 - Do we need to work on that? Current Deep NN backends compute the error gradient “automatically”
 - But, as Andrej Karpathy says, [Yes, you should understand backprop](#)

Computing the Gradient

- If w_{ij} is the weight connecting unit j to unit i , we have

$$\frac{\partial e^\ell}{\partial w_{ij}} = \frac{\partial e^\ell}{\partial a_i} \frac{\partial a_i}{\partial w_{ij}} = \frac{\partial e^\ell}{\partial a_i} o_j = \delta_i o_j$$

- In the output layer $e^\ell = \frac{1}{2}(y - \hat{y})^2$ and $a^O = \hat{y}$, and thus,

$$\delta^O = \frac{\partial e^\ell}{\partial a^O} = \frac{\partial e^\ell}{\partial \hat{y}} = \hat{y} - y$$

- Therefore, in the output layer we have

$$\frac{\partial e^\ell}{\partial w_h^O} = (\hat{y} - y) \frac{\partial a^O}{\partial w_h^O} = (\hat{y} - y) o_h^H$$

SHL Gradient Backprop I

- In the hidden layer we **backpropagate** the error $\delta^O = \hat{y} - y$:

$$\delta_h^H = \frac{\partial e^\ell}{\partial a_h^H} = \frac{\partial e^\ell}{\partial a^O} \frac{\partial a^O}{\partial a_h^H} = \delta^O \frac{\partial a^O}{\partial a_h^H} = (\hat{y} - y) \frac{\partial a^O}{\partial a_h^H}$$

- And since $y = a^O = \sum_h w_h^O o_h + b^O = \sum_h w_h^O \varphi(a_h^H) + b^O$,

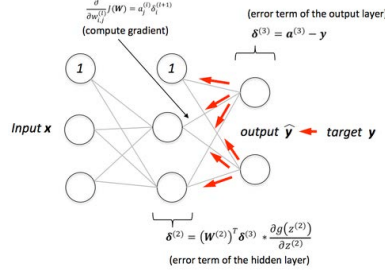
$$\frac{\partial a^O}{\partial a_h^H} = \frac{\partial a^O}{\partial o_h^H} \frac{\partial o_h^H}{\partial a_h^H} = \frac{\partial a^O}{\partial o_h^H} \varphi'(a_h^H) = w_h^O \varphi'(a_h^H)$$

- Moreover, $a_h^H = \sum_j w_{hj}^H x_j + b_h^H$, and

$$\frac{\partial e^\ell}{\partial w_{hj}^H} = \frac{\partial e^\ell}{\partial a_h^H} \frac{\partial a_h^H}{\partial w_{hj}^H} = \delta_h^H x_j = (\hat{y} - y) w_h^O \varphi'(a_h^H) x_j$$

SHL Gradient Backprop II

- Graphically we have the following scheme:



From [Sebastian Raschka's A Visual Explanation of the Back Propagation Algorithm for Neural Networks, KDnuggets](#)

Multiclass Log-Loss NN Classification

- Recall that our Logistic Regression model gave us estimate of $P(0|x; w_0, w)$, $P(1|x; w_0, w)$
- We then wrote the likelihood of a given sample as

$$P(Y|X; w_0, w) = \prod_{p=1}^N P(y^p|x^p; w_0, w)$$

- And then derived the optimum parameters w_0^*, w^* as

$$w_0^*, w^* = \arg \max_{w_0, w} P(Y|X; w_0, w)$$

- We can follow the same path for a K class classification problem:
 - We define MLPs $F(x; \mathcal{W}) \in \mathbf{R}^K$ so that $0 \leq F_k(x; \mathcal{W}) \leq 1$ and $\sum_k F_k(x; \mathcal{W}) = 1$
 - We assume that $P(k|x) \simeq F_k(x; \mathcal{W})$
 - We estimate \mathcal{W} by maximizing

$$P(Y|X; \mathcal{W}) = \prod_{p=1}^N \prod_{k=1}^K F_c(x^p; \mathcal{W})$$

1-hot Encoding and Posteriors

- The standard labelling of multiclass problems is the 1-hot encoding of class k by the vector $e_k = (0, \dots, \underbrace{1}_k, \dots, 0)$
- Then if $x \in C_k$, its label $y = (y_1, \dots, y_K)^t$ is e_k with $y_k = 1$ and

$$P(k|x) = P(k|x)^1 = P(k|x)^{y_k} = \prod_{c=1}^K P(c|x)^{y_c}$$

- Then for a sample $S = \{x^p, y^p = e_{c(p)}\}$ and a posterior model $P(c|x, w) = F_k(x, \mathcal{W})$, the probability of getting $S = (X, Y)$ is

$$P(Y|X; \mathcal{W}) = \prod_1^N P(c(p)|x^p; \mathcal{W}) = \prod_1^N \prod_{c=1}^K P(c|x^p; \mathcal{W})^{y_c^p}$$

The Cross Entropy Loss

- As before, we will work with the log-likelihood, i.e.

$$\begin{aligned} \ell(\mathcal{W}; S) &= \log P(Y|X; \mathcal{W}) = \sum_{p=1}^N \sum_{c=1}^K \log \left(P(c|x^p; \mathcal{W})^{y_c^p} \right) \\ &= \sum_{p=1}^N \sum_{c=1}^K y_c^p \log P(c|x^p; \mathcal{W}) \end{aligned}$$

- The **cross-entropy** loss is now simply the negative log-likelihood $-\ell(\mathcal{W}; S)$, i.e.,

$$L(\mathcal{W}) = -\ell(\mathcal{W}; S) = -\sum_{p=1}^N \sum_{c=1}^K y_c^p \log P(c|x^p; \mathcal{W})$$

- It is now straightforward to carry this into a NN setting

MLPs for Classification

- We consider an input layer and a number of hidden layers
- Targets are the 1-hot encodings of class labels, so we use K outputs
- We want the MLP's k -th output to estimate the posterior $P(k|x)$
- The natural output layer activation is thus the **softmax function**

$$\sigma_j(o) = F_j(x; \mathcal{W}) = \frac{e^{w_j \cdot o}}{\sum_1^K e^{w_k \cdot o}}$$

- Here o are the last hidden layer outputs
- w_j is the weight vector in \mathcal{W} which connects the last hidden layer with the network's j output
- For two classes this becomes $\sigma_1(o) = \frac{e^{w_1 \cdot o}}{e^{w_0 \cdot o} + e^{w_1 \cdot o}} = \frac{1}{1 + e^{(w_0 - w_1) \cdot o}}$
 - We thus get the **sigmoid activation** of Logistic Regression
- NN training reduces to the minimization of the cross entropy loss
- And the previous MLP discussion basically carries over to classification

Takeaways on Clasical MLPs

1. They have a layered structure with outputs computed in a **forward pass** using differentiable activations
2. Usual activations: ReLUs, sigmoid, tanh, linear
3. MLPs are **universal approximators**: this is indispensable for regression but has to be handled with care
4. MSE is the usual regression cost; we use a variant of cross entropy in classification
5. The error function gradients are computed by **backpropagation** of generalized errors
6. Backprop is basically a very simple procedure than can be **largely automated**
7. Once an MLP is defined (feedforward and backward passes), MLP training reduces to a (usually difficult and costly) **optimization problem**

4.2 Unconstrained Smooth Optimization

Back to Optimization

- To build a ML model \equiv to **minimize a loss function**
- General optimization theory is a key tool in Machine Learning (ML)
- There are two optimization set ups in ML
 - **Unconstrained** optimization, slightly simpler and the one used for MLPs
 - **Constrained** optimization, wider and more complex
- In ML we have also to consider the optimization of differentiable and also non differentiable error functions
- MLP optimization: **unconstrained and differentiable**
- And also **batch**, i.e., over the entire sample, **mini-batch** over subsamples or **on line**, pattern by pattern

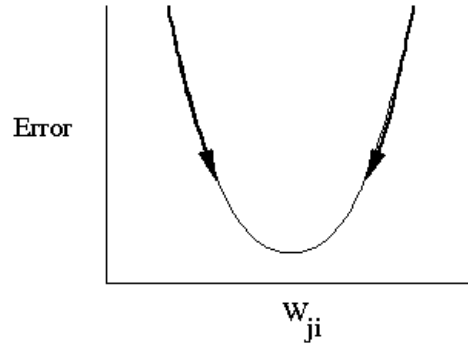
Gradient Descent

- We “stretch” the weight set \mathcal{W} into a vector w
- We recall that $-\nabla e(w)$ is the maximum descent direction
- First idea: to build a (hopefully convergent) sequence w^k iterating (small) steps along $-\nabla e(w^k)$

Gradient Descent II

- In more detail, we start from a random w^0 and compute

$$w^{k+1} = w^k - \rho_k \nabla_w e(w^k)$$



- ρ_k is the **learning rate** (LR)
- With a small ρ_k we ensure $e(w^{k+1}) < e(w^k)$ (although with possibly a very small descent)
- We can get a better iteration $w^{k+1} = w^k - \rho_k^* \nabla_w e(w^k)$ using a ρ_k^* given by

$$\rho_k^* = \arg \min_{\rho} e(w^k - \rho \nabla_w e(w^k));$$

this is known as **line minimization**

- These GD methods are called **first order methods** in part because they only use ∇e

One Dimensional Newton's Method

- Assume a quadratic function $q(w) = aw^2 + bw + c$, with $a > 0$, and a minimum at w^*
- We can reach w^* from any w with a step Δw such that

$$0 = q'(w + \Delta w) = 2a(w + \Delta w) + b$$

- We have thus $\Delta w = \frac{-b-2aw}{2a}$, that is,

$$w^* = w - \frac{2aw + b}{2a} = w - \frac{1}{q''(w)} q'(w)$$

- This leads to **Newton's method**: minimize a general f iteratively using steps

$$w^{k+1} = w^k - \rho_k \frac{1}{f''(w^k)} f'(w^k)$$

with ρ_k a suitable learning rate

One Dimensional Newton's Method II

- Notice how the $\frac{1}{f''(w_k)}$ acts as a **self adjusting learning rate**

- When the parabola is very sharp (i.e., $a \gg 1$), we will be close to the minimum and the descent can overstep it
- But then $f''(w_k)$ will be big and, hence, $\frac{1}{f''(w_k)}$ **moderates** the gradient step
- Conversely, when the parabola is very wide (i.e., $a \simeq f''(w_k) \ll 1$), the minimum will be far away and the gradient step small descent will
- But then $f''(w_k)$ will be rather small and, hence, $\frac{1}{f''(w_k)}$ **accelerates** the gradient step
- We can extend this to several dimensions

Multidimensional Newton's Method

- For a d dimensional w , the Taylor expansion of e at an optimum w^* is

$$e(w) \approx e(w^*) + \frac{1}{2}(w - w^*)^t \cdot \mathcal{H}(w^*) \cdot (w - w^*)$$

– $\mathcal{H}(w^*)$ is the **Hessian** of e at w^* and $\nabla e(w^*) = 0$

- It follows that $\nabla e(w) \approx \mathcal{H}(w^*) \cdot (w - w^*)$ and, therefore,

$$w^* \approx w - \mathcal{H}(w^*)^{-1} \nabla_w e(w)$$

- This suggest to derive the w^k by

$$w^{k+1} = w^k - \rho_k \mathcal{H}(w^k)^{-1} \nabla_w e(w^k)$$

which is known as **Newton's Method** (NM)

Variants of Newton's Method

- Theoretically NM converges very fast near w^* , but
 - Far from w^* convergence is not guaranteed
 - Moreover $\mathcal{H}(w^k)$ may not be invertible
 - Besides, computing $\mathcal{H}(w^k)$ is cumbersome and costly
- Near the minimum the **Gauss-Newton (GN)** approximation

$$\mathcal{H}(w) \simeq E[\nabla e(w) \nabla e(w)^t],$$

holds for any quadratic cost and simplifies the third problem

- The **Levenberg-Marquardt (LM)** method deals with the other two problems combining
 - Gradient descent “away” from w^*
 - Gauss-Newton “near” w^*

although “away” and “near” have to be properly addressed

One-dimensional GN Approximation

- Assume $e(w) = \frac{1}{2} \int (f(x; w) - y)^2 p(x, y) dx dy$; then

$$\begin{aligned} e'(w) &= \int (f(x; w) - y) \frac{\partial f}{\partial w}(x, y) p(x, y) dx dy; \\ e''(w) &= \int \left(\frac{\partial f}{\partial w} \right)^2 p(x, y) dx dy \\ &\quad + \int (f(x; w) - y) \frac{\partial^2 f}{\partial w^2}(x, y) p(x, y) dx dy \end{aligned}$$

- Near a minimum w^* we may expect $f(x; w) \simeq y$ and, therefore,

$$e''(w) \simeq \int \left(\frac{\partial f}{\partial w} \right)^2 p(x, y) dx dy > 0$$

- Thus, for square errors, we can use first derivatives to approximate $e''(w)$

General GN Approximation I

- In the general case we have

$$\nabla e(w) = E [\nabla f(x; w) (f(x; w) - y)]$$

- And, therefore,

$$\begin{aligned} \nabla^2 e(w) &= E [\nabla^2 f(x; w) (f(x; w) - y)] + \\ &\quad E [\nabla f(x; w) \nabla f(x; w)^\tau] \end{aligned}$$

- The second term is easy to compute once we have ∇f
- If $w \approx w^*$, $f(x; w) \approx y$; therefore $f(x; w) - y \approx 0$,
 - We can ignore the first, more complex, term

General GN Approximation II

- We arrive at $\nabla^2 e(w) \simeq E [\nabla f(x; w) \nabla f(x; w)^\tau]$ or, equivalently,

$$\mathcal{H}_{(i,j)(p,q)}(w) = \left(\frac{\partial^2 e}{\partial w_{ij} \partial w_{pq}}(w) \right) \simeq \left(E \left[\frac{\partial f}{\partial w_{pq}} \frac{\partial f}{\partial w_{ij}} \right] \right)_{(i,j)(p,q)}$$

- $\mathcal{J} = E [\nabla f(x; w) \nabla f(x; w)^\tau]$ is **Fisher's information matrix**
 - \mathcal{J} is **semidefinite positive**

- And thus not necessarily invertible
- Often only its diagonal is considered and we have

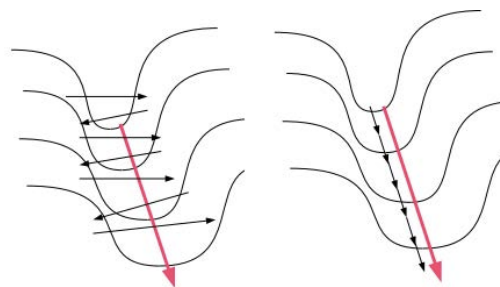
$$\mathcal{H}_{(i,j)(i,j)}(w) = \left(\frac{\partial f}{\partial w_{ij}} \right)^2$$

Advanced Optimization

- There are many more proposals in unconstrained optimization
- The **Conjugate Gradient** (CG) and **Quasi-Newton** (QN) methods are important in classical MLP training
- The basic idea in CG is to replace gradient descent directions $g_k = -\nabla e(w_k)$ with new conjugate directions that try to keep somehow the previous “good directions”
- The basic idea in QN is to iterate as in NM but with simple approximations \mathcal{A}_k to $\mathcal{H}^{-1}(w^k)$ that converge to $\mathcal{H}^{-1}(w^*)$
- When training “small” NNs the **Limited-memory Broyden-Fletcher-Goldfarb-Shanno** (L-BFGS), a QN variant, is often used

Accelerating Gradient Descent

- A possibility on the error surface of a NN is to have many long, narrow ravines
 - Gradients bounce in the narrow section, but may be very small along the wider one



Momentum

- **Momentum** pushes them forward in the wider section (but we have to cope with a new parameter)
- Momentum tries to maintain descent’s inertia with a term $\Delta^k = w^k - w^{k-1}$, i.e.,

$$w^{k+1} = w^k - \rho_k \nabla_w e(w^k) + \mu_k \Delta^k$$

- More or less, what a **heavy ball** would do

- The goal is to keep w^k advancing in “plateaux”, i.e., small gradient zones
- Momentum can be seen as a crude approximation of a CG step
- Nice explanation at [Why Momentum Really Works](#)

Nesterov’s Accelerated Gradient

- Let’s rewrite momentum in two steps

1. Define $\Delta^{k+1} = -\rho_k \nabla_w e(w^k) + \mu_k \Delta^k$ and

2. Apply

$$w^{k+1} = w^k + \Delta^{k+1} = w^k - \rho_k \nabla_w e(w^k) + \mu_k \Delta^k$$

- Nesterov’s Accelerated Gradient is a variant of this

$$\begin{aligned}\tilde{\Delta}^{k+1} &= -\rho_k \nabla_w e(w^k + \mu_k \tilde{\Delta}^k) + \mu_k \tilde{\Delta}^k; \\ w^{k+1} &= w^k + \tilde{\Delta}^{k+1}\end{aligned}$$

- In convex optimization it improves GD and is often highly effective in Deep Network training

Adam

- Adam is currently the most widely used gradient-descent method for deep NN training
- At each step t Adam uses a new random mini-batch to
 - Update exponentially smoothed averages m_t of the gradient g_t and v_t of the squared gradient $g_t^2 = g_t \odot g_t$ as

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t, \quad v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2;$$

- Compute bias corrections \hat{m}_t, \hat{v}_t as

$$\hat{m}_t = \frac{1}{1 - \beta_1^t} m_t, \quad \hat{v}_t = \frac{1}{1 - \beta_2^t} v_t;$$

- Update weights as $W_t = W_{t-1} - \alpha \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$

- One can show $E[m_t] \simeq (1 - \beta_1^t) E[g_t]$ and $E[v_t] \simeq (1 - \beta_2^t) E[g_t^2]$
- Default values $\alpha = 0.001, \beta_1 = 0.9, \beta_2 = 0.999$, and $\epsilon = 10^{-8}$ usually work fine

Understanding Adam

- What is going on in Adam?
- At each step we work with estimates of the average local gradient:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \simeq E[\nabla_w f];$$

- Then $v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \simeq E[(\nabla_W f)^2] \simeq \sigma(g_t)$
- Thus, we can see Adam as a kind of “normalized” gradient descent
- Or since we can expect $E[(\nabla_W f)^2] \simeq E[\nabla_{W^2}^2 f]$, we can see Adam as a “cousin” of diagonal Gauss–Newton’s steps

When to Stop Training

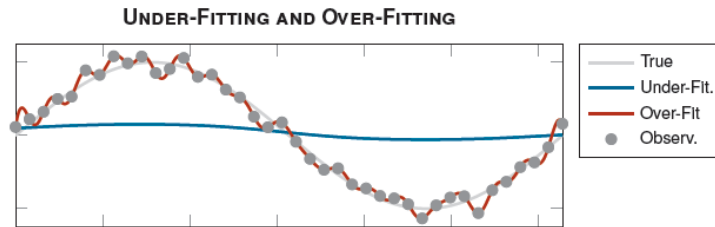
- Typically the $e(w_k)$ error diminishes towards an asymptotic minimum
 - If many units are used, we arrive to 0, which usually implies overfitting
- First solution: to use a separate **validation subset** V and stop training when the error in V , i.e., the **validation error** starts growing
 - But: How to choose V ? What do we do for small samples?
- Second solution (better): **get a good regularization** (and forget about overfitting)
 - A low CV error is also a low validation error
 - Now training stops because of reasons such as computational cost, but not because of overfitting risk

Takeaways on MLP Optimization

- **Gradient descent** is the simplest method but possibly also the slowest
- **Momentum** can be used to speed it up
- **Newton’s method** is much faster but may be very costly and difficult to apply in full form
- All the previous methods require the (usually tricky) selection of a **learning rate**
- Second order methods such as Conjugate Gradient and **Quasi–Newton** avoid learning rates and are more efficient but costlier
- **Limited Broyden–Fletcher–Goldfarb–Shanno** (L-BFGS) is currently the option of choice for “small” MLPs

Overfitting in MLPs

- Since MLPs are a UAF, they can also approximate the noise in the sample
 - Given $S = \{(x^p, y^p)\}$ if we allow enough hidden units in a SHL MLP we can arrive to a w^* s.t. $y^p = f(x^p; w^*)$
 - We get thus a sample error $\hat{e}(w^*) = 0$ but possibly with a very high generalization error
- I.e., MLPs may have very small bias but possibly large variance



(Ph.D. Thesis of Carlos Alai z)

Regularization vs Overfitting

- Why is there overfitting?
 - Because we may end up having too many weights with respect to sample size
 - Because we allow these weights to explore the entire weight space
- We can avoid this wandering if we limit w 's growth, for which we add a **regularization** term $g(\|w\|)$ to $e(w)$ with $g(r)$ increasing
- Working with $e_R(w) = e(w) + g(\|w\|)$ we have to **balance** the minimization of $e(w)$ and that of $g(\|w\|)$
- This balanced learning results in better generalization

L_2 Regularization

- The simplest regularization procedure adds a quadratic penalty to the square error e

$$e_R(w) = e(w) + \frac{\lambda}{2} \|w\|^2,$$

with λ the **weight decay** factor

- Also known as Tikhonov's regularization (or Ridge Regression for linear models)
- The desired effect is to constrain the evolution of w :
 - In fact, the regularized loss is essentially the **Lagrangian of the constrained problem**

$$\min_w e(w) \text{ subject to } \|w\|^2 \leq \rho, \quad \rho > 0$$

- The gradient becomes $\nabla e_R(w) = \nabla e(w) + \lambda w$
- And the Hessian is $\mathcal{H}_R(w) = \mathcal{H}(w) + \lambda I$

Regularized Algorithms

- The preceding methods apply straightforwardly to e_R
- Gradient descent becomes

$$w^{k+1} = w^k - \rho_k (\nabla_w e(w^k) + \lambda w^k)$$

- Newton steps are now

$$w^{k+1} = w^k - \rho_k (\mathcal{H}(w^k) + \lambda I)^{-1} (\nabla_w e(w^k) + \lambda w^k)$$

- And the Gauss–Newton approximation to $\mathcal{H}_R(w)$ is

$$\mathcal{H}_R(w) = \mathcal{H}(w) + \lambda I \sim E[\nabla f(w) \nabla f(w)^T] + \lambda I$$

that is **definite positive** and, hence, **invertible**

How to choose λ

- Again, the correct choice of λ is crucial
- A small $\lambda \ll 1$ results in a small regularization effect and overfitting risk appears
- A large $\lambda \gg 1$ causes learning to forget about $e(w)$ and the model will be essentially constant and will underfit
- Usually λ is chosen by using CV by exploring a discrete set of values λ_j ,
- The same can essentially be done for any other hyper-parameter: number of hidden layers? number of hidden units? learning rate?? minibatch size??

MLP Ensembles

- Recall that $e(w)$ does not have a single minimum
- Moreover, the final MLP depends on the random initial w^0
- And mini-batch training adds extra randomness to the final model
- This suggests
 - To start from K independent initial weights and get K optimal weight sets w_k^*
 - To output the average $f_e(x) = \frac{1}{K} \sum_1^K f(x; w_k^*)$
- We expect outputs of the form $\hat{y}_k^p = y^p + \epsilon_k^p$ with the ϵ_k^p independent
- Hence $\frac{1}{K} \sum_k \epsilon_k^p \simeq 0$ and $\frac{1}{K} \sum_k \hat{y}_k^p \simeq y^p$

Takeaways on MLP Regularization

- MLPs have a **high risk of overfitting**
- Thus, they must be **regularized** to avoid overfitting

- The regularization hyperparameter is chosen through **cross validation**
- MLP training has two **random components**: the initial point and minibatch selection
 - Thus, each training will converge to a **different optimum**
- MLP **ensembles** can take advantage of this
 - They imply extra costs but ensembles are **embarrassingly parallelizable**

4.3 Computational Costs of MLPs

MLPs and Big Data?

- Many Vs in Big Data: **Volume, Velocity**, Variety, Veracity, Value, ...
- Velocity: information flows in data streams that require fast processing and feed back
 - MLPs are rather fast
 - Less than linear models but much more so than SVMs
- Volume is probably the greatest attractive of Big Data
 - Huge samples and/or very large pattern dimension
 - Large impact in model training

Volume in MLPs

- Parallelism is the first answer to Big Volume
- On a standalone machine it may be
 - Passive: let the SO distribute work among several CPU cores, or use GPUs with low level parallelized libraries such as Linpack or BLAS for linear algebra
 - Active: explicitly exploit a problem's parallelism programming an algorithm in, say, OpenMP
- It is easy to passively parallelize the training of several MLPs
 - But memory costs multiply
- Training an isolated MLP is not CPU parallelizable:
 - There is a sequential layer dependence in Backprop
 - Each training iteration depends on the previous one
 - But matrix-vector multiplications can exploit GPU parallelism

Handling Huge Sample Training

- Two consequences of a large N are
 - Sample doesn't fit in memory and we have to split it somehow

- Training gets “lost”, for in the global gradient $\nabla e = E[\nabla e^\ell]$ we average many local gradients that may cancel each other out
- The first problem has been always present in fields such as analog signal filtering
- Solution for both: adaptive or **on line**, i.e., pattern by pattern, weight updates
 - It also allows a relatively simple setting for a theoretical analysis
 - But not used today; instead, medium-to-large NNs are trained using **mini-batches**

MLP Complexity

- MLPs are fast to apply but costly to train
- How can we estimate this cost?
- MLP training cost is determined by
 - Its **architecture**, that determines the number of weights to fit and that is also dependent on the input dimension D
 - The full or mini-batch **sample size** N , that determines the cost of the averages to be computed
 - The **training method**, with more or less iterations that, in turn, are more or less costly

Forward Pass Complexity

- The number of weights in a single hidden layer (SHL) MLP with D inputs, one output and one hidden layer with H units is

$$(D + 1) \times H + (H + 1) \simeq HD$$

- Each extra hidden layer pair with (H_1, H_2) units adds $(H_1 + 1) \times H_2 \simeq H_1 H_2$ weights
- For a general MLP the cost in floating point operations of a forward pass is $\simeq N \times (\sum_h H_h \times H_{h-1})$
 - Very fast on GPUs as it theoretically becomes $O(N \times \sum_h H_h)$

The Cost of Computing ∇e^ℓ

- Computing a local gradient ∇e^ℓ in a SHL MLP with square error and one output essentially requires to compute
 - H components for the hidden to output connections, with a $O(1)$ cost each, for $\frac{\partial e^\ell}{\partial w_h^O} = (\hat{y} - y) o_h$
 - DH components for the input to hidden connections with essentially an $O(1)$ cost each, for $\frac{\partial e^\ell}{\partial w_{h,j}^H} = \left(\sum_{i=1}^L \delta_i w_{ih}^O \right) \sigma'(a_h) x_j$
- In these we are omitting the partials with respect the bias, but they are much less

- Thus, the overall cost of computing ∇e^ℓ is essentially $O(DH)$
- More layers with H_h units add a cost $O(H_{h-1} \times H_h)$
 - $O(\sum_h H_h)$ on GPUs

The Cost of Computing ∇e

- For a mini-batch of size N_b , the cost of the mini-batch gradient ∇e of a SHL MLP is $O(N_b \times D \times H)$
- And extra layers add a cost $O(N_b \times H_{h-1} \times H_h)$
- This is of the same order of magnitude than the cost of the forward pass
- This also dominates the $O(H_{h-1} \times H_h)$ cost of updating the (H_{h-1}, H_h) weights in gradient descent
- And all these costs have to be multiplied by the number of training **epochs**

Training Complexity

- The important term in the overall training cost is $\text{nEps} \times \text{cost of } \nabla e$, with nEps the number of epochs
 - One epoch = one pass on the entire sample
- Thus, the **globally dominant term** in a SHL MLP is

$$\text{nEps} \times \text{cost of } \nabla e = O(\text{nEps} \times N \times D \times H)$$
 with N here the entire sample size
- And an extra cost

$$O(\text{nEps} \times N \times H_{h-1} \times H_h)$$
 for extra hidden layers
- Thus, training many layered, large MLPs can be **very costly**
 - But **linear in sample size N**

Takeaways on MLP's Cost

- MLP complexity is determined by its **architecture $\{H_h\}$, training procedure and sample size N**
- The forward and backward MLP passes have basically the **same complexity**
- Their cost per **pattern and layer** is $H_{h-1} \times H_h$
- For gradient descent these costs are **multiplied by the number nEps of epochs**
- First order methods essentially **do not add extra complexity**
- Second order methods add extra per iteration costs but should **require less iterations**
- Single MLP training is **not CPU parallelizable**
- But **GPUs** can greatly improve MLP processing costs

4.4 Convergence of MLP Training

Handling Huge Sample Training

- Two consequences of a large N are
 - Sample doesn't fit in memory and we have to split it somehow
 - Global gradient is no longer feasible and we have to exploit its average $\nabla e = E[\nabla e^\ell]$ over local gradients
- The fist problem has been always present in fields such as analog signal filtering
- Solution: adaptive or **on line**, i.e., pattern by pattern, weight updates
 - Not used today: Currently medium-to-large NNs are trained using **mini-batches**
 - But allows a relatively simple setting for a theoretical analysis

Adaptive Filtering

- The signal processing solution to not having storage: **adaptive lineal filters** (ADALINE)

$$\begin{aligned} w^{k+1} &= w^k - \rho_k (\hat{y}_k - y_k) X^k \\ &= w^k - \rho_k \nabla e^\ell(X^k, y_k; w^k) \end{aligned}$$

- This is just local gradient descent in linear regression
- This makes sense also for MLPs
- On Line Learning \equiv local gradient descent

On Line Learning of MLPs

- Starting from w^0 , at time $\tau = 1, 2, \dots$
 - We get a random pattern $x^p = x^{p(\tau)}$ and its target target y^p
 - we compute $\hat{y}^\tau = F(x^p, w^\tau)$ and $\nabla e^\ell(x^p, y^p; w^\tau)$
 - We update $w^{\tau+1} = w^\tau - \rho_\tau \nabla e^\ell(x^p, y^p; w^\tau)$
- The Single Hidden Layer MLP complexity is now $O(\text{nIters} \times DH)$ and $\text{nIters} > N$ is to be expected:
 - A batch epoch has the same cost of N on line iterations
- But now we do not have to store or even to know the entire sample
- And N on line iterations usually are more effective than a batch epoch

Variants in On Line Learning

- It is straightforward to include quadratic regularization

$$w^{\tau+1} = w^{\tau} - \rho_{\tau} (\nabla e^{\ell}(x^p, y^p; w^{\tau}) + \lambda w^{\tau})$$

- As well as momentum

$$w^{\tau+1} = w^{\tau} - \rho_{\tau} \nabla e^{\ell}(x^p, y^p; w^{\tau}) + \mu_{\tau} \Delta^{\tau}$$

- Moreover the MLP is constantly updated
- We can work with **minibatches** with a fixed number of patterns instead of isolated ones
 - The same tricks and stopping criteria of batch learning apply and also CG is often possible over minibatches
- But: is there convergence?

Learning as a Random Variable Evolution

- In on line learning
 - The initial weight w^0 is random
 - The pattern $x^{p(t)}$ received at time t is also random
- Thus, the sequence w^t is a **realization of a random variable** W^t
- We have deal with random variable convergence theory ...
- Rather heavy going, with many, more or less related, definitions

Convergence of Random Variables

- The basic limit concepts have to be adapted when dealing with random variables
- Set up: probability space (Ω, \mathcal{A}, P)
- Pointwise limits are trickier so one starts with mean convergence
- $X_n \rightarrow X$ **in the r -th mean**, $r \geq 1$, (usually $r = 2$ or $r = 1$) if

$$E_P[|X_n - X|^r] = \int |X_n(\omega) - X(\omega)|^r dP(\omega) \rightarrow 0$$

- For a general probability space (Ω, \mathcal{A}, P) and suitable f , $E_P[f] = \int f(\omega) dP(\omega)$ can be properly defined
- Situation here: ω is given as a feature vector x and dP has a density $p(x)$; the previous definition becomes

$$E_P[|X_n - X|^r] = \int |X_n(x) - X(x)|^r p(x) dx \rightarrow 0$$

Pointwise Convergence of Random Variables

- We say $X_n \rightarrow X$ **almost surely** (AS) if

$$P(\{\omega : \lim X_n(\omega) = X(\omega)\}) = 1$$

- It is the closest to the standard pointwise convergence
- Has many synonyms: convergence **almost everywhere, strongly** or (slightly confusing) **with probability 1**

- An equivalent definition is that for all $\epsilon > 0$

$$\lim_n P(\{\omega : \sup_{m \geq n} |X_m(\omega) - X(\omega)| \geq \epsilon\}) = 0$$

- We say $X_n \rightarrow X$ **in probability** if for all $\epsilon > 0$

$$\lim P(\{\omega : |X_n(\omega) - X(\omega)| \geq \epsilon\}) = 0$$

- Convergence AS is thus stronger than convergence in probability
- In fact, convergence AS surely implies convergence in probability

Convergence in Distribution

- We say $X_n \rightarrow X$ **in distribution** if $\lim F_{X_n}(x) = F_X(x)$ at every x where F is continuous
- Synonyms: convergence **in law** or **weakly**
- The continuity requirement aims to avoid degenerate cases
 - If $X_n = \chi_{[0, 1/n]}$, they converge in distribution (and pointwise) to $X \equiv 0$, for which $F_X(0) = 1$ while $F_{X_n}(0) = 0$
 - But 0 is not a point of continuity of F_X
- Convergence in distribution does not imply convergence of the density functions
- But convergence of the density functions implies convergence in distribution
- **Lévy's Theorem:** the sequence X_n converges in distribution to X iff the sequence of corresponding characteristic functions ϕ_n converges pointwise to the characteristic function ϕ of X

Relationships

- Recall that convergence almost surely implies convergence in probability
- Convergence in probability implies convergence in distribution
- Convergence in the mean for $r \geq 1$ implies convergence in probability (by Markov's inequality)

- If $r > s \geq 1$, convergence in the r -th mean implies convergence in the s -th mean
- Convergence in probability (and, hence, in the mean) implies convergence a.s. for some subsequence X_{n_k}
- If the X_n are bounded by an integrable Z and converge a.s. to X , they also converge in the r -th mean
- But the other implications are false

Limit Theorems

- **Weak Law of Large Numbers:** if the X_n are i.i.d., then the sample mean $\bar{X}_N = \frac{1}{N} \sum_1^N X_n$ converges in probability (weakly) to $\mu = E[X_n]$
- **Strong Law of Large Numbers:** if the X_n are i.i.d., then the sample mean $\bar{X}_N = \frac{1}{N} \sum_1^N X_n$ converges a.s. (strongly) to $\mu = E[X_n]$
- Besides weaker, the weak LLN is easier to prove
- **Central Limit Theorem:** if the X_n are i.i.d. with mean μ and variance σ^2 , then the random variable $\sqrt{N}(\bar{X}_N - \mu)$ converges in distribution to a Normal $N(0, \sigma^2)$
- The LLN tells us that the sample mean converges; the CLT tells us how the sample mean error (approximately) behaves

Convergence of On Line Learning

- The end result for MLP on line learning is that the random variable sequence W^t converges in mean square to an w^* s.t. $0 = \nabla e(w^*)$
- That is, w^* is (very likely) a local minimum of e
- Theoretical foundation in the **Strong Law of Large Numbers:**
If the X^n are i.i.d., then the sample mean $\bar{X}_N = \frac{1}{N} \sum_1^N X^n$ converges a.s. (strongly) to $\mu = E[X^n]$

Stochastic Optimization (SO)

- In a deeper look, assume the following:
 - We want to solve the equation $g(w) = 0$ that has a single root w^*
 - Where we don't know $g(w)$...
 - But can get an **oracle**, i.e., a random estimate $\hat{g}(X^n, w)$ with X^n i.i.d. such that $E[\hat{g}(X, w)] = g(w)$.
- Then, starting at a random variable W^0 and for some sequence ρ_k , we define random variables

$$W^{k+1} = W^k - \rho_k \hat{g}(X^k, W^k)$$

and hope for the best

Robbins–Monro SO

- Robbins and Monro showed that $W^k \rightarrow w^*$ in square mean (and, hence, in probability) if (among others)
 1. g is non decreasing and $g'(w^*) > 0$,
 2. $\sum \rho_k = \infty, \sum \rho_k^2 < \infty$
- For a D dimensional extension we assume the Jacobian $J_g(w^*)$ to be positive definite
- We need a dictionary to translate this to on line MLP training
- But first let's try to understand it on a simple situation

Why it Works?

- Assume we want to solve the equation $g(w) = w - \mu$ where we do not know μ , but can get random estimates $\hat{g}(X_n, w) = w - X_n$ with X_n i.i.d. s.t. $E[X_n] = \mu$
- It is obvious that $E[\hat{g}(X, w)] = g(w)$
- Then, starting at $W_0 = 0$ and for $\rho_k = \frac{1}{k+1}$, let's define

$$W_{k+1} = W_k - \frac{1}{k+1}(W_k - X_{k+1});$$

- Then, unwinding the recurrence we arrive at

$$W_{k+1} = \frac{1}{k+1} \sum_{j=1}^{k+1} X_j,$$

which, by the LLN converges to the root $\mu = E[X]$ of $w - \mu = 0$

- Thus Robbins–Monro essentially reduces here to the LLN

Stochastic Optimization and MLPs

- We begin with $e(w) = E[e^\ell(\cdot, w)]$, which is smooth with (we hope) a minimum w^*
- As g we take $g(w) = \nabla e(w) = E_X[\nabla e^\ell(x, w)]$ (unknown) and $\hat{g}(x, w) = \nabla e^\ell(x, w)$ (known)
- Then we have $E_X[\hat{g}(x, w)] = g(w)$
- Its Jacobian $J_g(w) = \mathcal{H}_e(w)$ is definite positive at and near w^*
- Starting at a random W^0 we take the X^k as i.i.d. and build the r.v. sequence for appropriate ρ_k

$$W^{k+1} = W^k - \rho_k \nabla e^\ell(X^k, W^k)$$

- Robbins–Monro then ensures that the W^k converge in mean square to an w^* s.t. $0 = g(w^*) = \nabla e(w^*)$, which by local convexity must then be a minimum of e

Takeaways on Online Learning

1. Training standalone MLPs is difficult to parallelize (or to be done under a MapReduce scheme)
2. On the other hand, simple parallel training of several MLPs is very easy
3. Very large samples require on line or (usually) mini-batch training
4. Theoretical results on Stochastic Gradient Descent imply convergence (in a random variable sense)
5. But training may be slow and unstable
6. And choosing the right learning rate may be tricky

4.5 Deep Networks

NN's Second Spring

- There was a very intense academic interest in the (by now) standard MLPs in the 1990's
 - Several NN conferences and journals appear
- MLP working and training became well understood
 - Although losing much of neuronal plausibility
- MLPs found relevant applications in many fields
 - They were incorporated into data science tools and products
 - Although hyperparameter selection was (is) costly and had (has) to be done very carefully

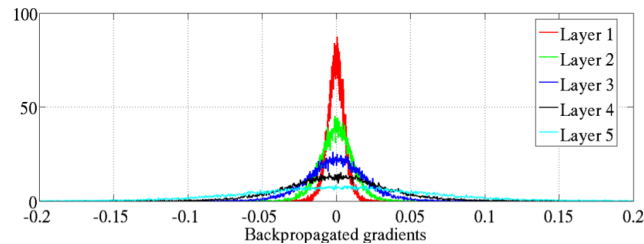
NN's Golden Autumn?

- This went on strongly until the late 90's when
 - New relevant contributions decreased
 - New competitors appeared: Boosting, SVMs, Random Forests, Gradient Boosting Regression, ...
- A nagging issue were deeper MLPs
 - One hidden layer MLPs were enough for most applications
 - But nobody knew how to train MLPs with three or more hidden layer

Vanishing Gradients

- One main obstacle was **vanishing gradients**:

- Consider the weight distribution in a 5 layer MLP



From Glorot & Bengio, AISTATS 2010

- Gradients in the last (5–th) layer are nonzero but vanish as we go back towards the first layer
- Training ceases to have any effect and learning stalls at an early, bad minimum

Towards Deep Networks

- Deep Nets: (initially) standard MLPs with 3 or more layers, either fully connected or **convolutional**
- Training impossible even in early 2000:
 - Poor results over limited HW
 - Addressable problems better solved by single layer nets
- First breakthrough around 2007: deep MLP **unsupervised pretraining** using stacked RBMs (Hinton) or autoencoders (Bengio)
- Easier fine-tuning afterwards by standard backprop

Renewed Interest

- Interest in NNs was rekindled and around 2010 the floodgates opened:
 - Large nets with huge number of weights
 - New convolutional layers, regularizations, initializations or activations
 - New techniques appear ... that are not that different from the old ones
- **New mood**: what was impossible before is now much easier and leads to better results
- Major breakthroughs were achieved in significant problems in computer vision and speech recognition

The Boom

- Things go from a mild NN stagnation around 2000 to big explosion in the 2010s

- Relatively large number of contributions and widely attended workshops in mayor conferences (ICML, NIPS)
- Strong groups in leading companies (Google, Baidu, Facebook, Microsoft)
- Great scientific (and mediatic) success: [Deep learning. LeCun, Bengio & Hinton \(Nature, May 2015\)](#)
- New field arising: **Representation Learning**
- New (possible and perhaps more plausible) connections with computational neuroscience (at least for image and audio recognition?)

What Is New In DNNs?

- New and fancy network structures:
 - Convolutional layers (with non-differentiable components)
 - More flexible feedforward connections
- **Automated symbolic backprop derivation**
- Network size: huge number of weights
- Very large sample size (sometimes)
- Many different new cost functions
- New (non differentiable) activations: **ReLU**s
- New regularization: **dropout**, dropconnect
- Recognition that a **good weight initialization is critical**

Changes In DNN Training

- Some things have to change:
 - Batch training becomes unfeasible for huge samples/networks
 - Strict online learning may become impractical as single patterns may get lost in huge samples and networks
- Minibatch training balances these extremes:
 - Choose a minibatch size M (a new DNN parameter?) and at each iteration randomly select M sample patterns
 - Perform SGD or some variant over the minibatch
 - Or even a second order method such as CG

Changes In DNN Training II

- But others do not

- Backprop is still the backbone of gradient computation
 - But it is no longer programmed but derived automatically by **symbolic differentiation**
 - Easily extended to convolutional layer weights
 - Imaginatively extended to non-differentiable elements: just pretend that they are so!
- Minibatch-based Stochastic Gradient Descent (SGD) still is the primary optimization approach
- And several hyper-parameters may still have to be chosen, with no clear cut procedures

Training Time and Technology

- Training time is a key issue as it usually shoots up:
 - Samples may be very large
 - Networks may be huge even for moderate samples
 - More hyperparameters may have to be optimized
- Heavy duty computing needed:
 - Multicore machines: very handy for hyperparameter selection; less so for single network training
 - Same true for cloud computing environments
 - GPUs: excellent for single network training
- Best: machines/computing centers with many GPUs

Ad Hoc Programming Tools

- Do-it-yourself programming no longer possible
- Increasingly better tools are being available with very fast evolution
- Initially PyLearn+Theano
- Next [Caffe](#): C++ base with Python interface
- Now [Keras](#): Python platform capable of running on top of Theano and Google's TensorFlow
- Plus open releases by large companies
 - Google's TensorFlow (plus TensorBoard)
 - Facebook's Torch, on top of the Lua language
 - Twitter's Autograd for Torch (improving its automatic differentiation capabilities)

New and Fancy New Deep Architectures

- The layers of a feedforward net are nodes in a linear chain graph
 - Backprop is straightforward on such a graph
- But it is also very easy in nets with layers in a DAG
 - They connect different input nodes to different outputs at varying depths and with different layer processing
 - The backprop path is also straightforward
 - And the backprop components at each layer node can be “collated” to the full network gradient
- We just “program” the DAG net defining layer nodes and connecting them in a DAG
 - Then a compiling step yields the forward pass and the backward gradient
- End result: fairly fancy networks
 - Perhaps useful; certainly very costly to train

And Much Better Technologies

- Advanced hardware is a must:
 - GPUs, multicore machines, cloud
- High-level programming:
 - Python as data preprocessing/pipelining + DNN model definition + experimental setup setting + results visualization
 - Python based high-level layers to symbolic GPU backends: Keras (coding in Python), TensorBoard (point and click?)
 - Git as the code and ideas exchange tool
- Also, and very important, new ideas on **initialization, regularization, architectures and learning methods**

Initialization

- If layers with M_i units used, the standard **Glorot–Bengio** (xavier) procedure is

$$W_i \sim U \left[-\frac{\sqrt{6}}{\sqrt{M_i + M_{i+1}}}, \frac{\sqrt{6}}{\sqrt{M_i + M_{i+1}}} \right]$$

- It ensures $Var \left(\frac{\partial e}{\partial w_i} \right) \simeq Var \left(\frac{\partial e}{\partial w'_i} \right)$ across successive layers when tanh activations are used
- Gradient vanishing is thus avoided
- **He**’s initialization recommended for ReLU activations

- Pretraining no longer indispensable (at least for large training data sets)

Dropout Regularization

- The extremely large weight numbers of Deep Neural Networks (DNNs) make regularization mandatory
- First choice: standard Tikhonov regularization (i.e., **weight decay**) for regression DNNs with linear output units
- **Dropout** in other fully connected layers, replacing standard output processing $o_i^\ell = f(a_i^\ell) = f(w_i^\ell o^{\ell-1} + b_i^\ell)$ by

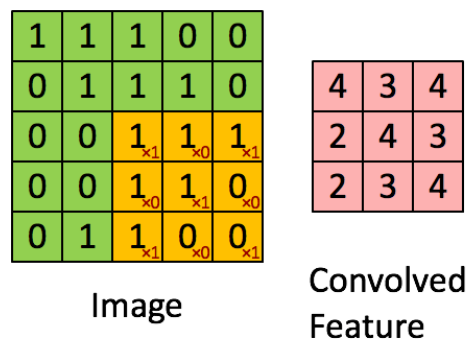
$$o_i^\ell = f(a_i^\ell) = f(w_i^\ell(o^{\ell-1} \odot r^\ell) + b_i^\ell),$$

with each r_j^ℓ being 1 with probability p

- It somehow sub-samples a larger network at each layer
- Output errors are backpropagated but the final optimal weights w^* are **downscaled** as $w_f^* = pw^*$
- It adds **randomness** to the final DNN model (and some **independence** for two different models)
- Output errors are backpropagated but the final optimal weights w^* are downscaled as $w_f^* = pw^*$

Convolutional Layers

- Starting assumption: patterns organized in features having a one-, two- or multi-dimensional structure
- Basic processing: to apply a $K \times K$ convolutional filter w over an image patch x_j as $y_j = f(w * x_j + b)$



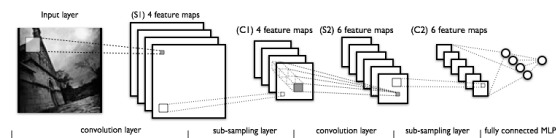
From [Stanford's UFLDL Tutorial](#)

Convolutional Layers II

- An $M \times N$ input “image” x is transformed into an $(M - K + 1) \times (N - K + 1)$ output $x' = C(x)$
- This is done over Q input **feature maps** x_1, \dots, x_Q and creates R output feature maps x'_1, \dots, x'_R
- Then a **pooling** transformation $P(x')$ over $K' \times K'$ patches of each x'_j
 - Possible pooling transforms: averages, max
- We have to learn $Q \times R$ pairs of $K \times K$ filters (w_ℓ, b_ℓ)
 - And decide on K, K' and the pooling transformation
- The forward pass has a cost of $O(Q \times M \times N \times K^2 \times R)$ per pattern, which can be quite costly

Deep Convolutional NNs

- Important goals may be achieved: invariance preservation, structural feature extraction, balancing layer sizes
- Deep Convolutional NNs combine the previous steps
 - An initial number of convolutional layers, followed by
 - A number of fully connected inner product layers and, finally
 - A readout layer that yields the NN’s response



A typical architecture for image processing. From [Convolutional Neural Networks \(LeNet\)](#) tutorial

- Possibly with connections and weights in the millions

New Optimization Techniques

- Second order methods across iterations are only possible over small minibatches
- New ideas have been progressively introduced
 - Either refinements of previous approaches more or less sidelined: **Rprop, momentum a la Nesterov**
 - Or often borrowed from other optimization contexts: **Adagrad, Adadelata, Adam**

- Or simply (overlooked) common sense: minibatch training
- Two main goals:
 - To shorten computation time (obviously)
 - To simplify hyperparameter handling and selection (even more so!)

Takeaways in Deep Networks

1. **Right initialization** crucial
2. **ReLU**s as new activation function
3. Alternative **dropout** regularization for fully connected layer regularization
4. **Convolutional layers** to be used on structured inputs (but processing much costlier)
5. **New optimization** ideas (Adagrad, Adadelta, Adam) to simplify handling of learning rates
6. **Heavy duty computing** environments, particularly for hyperparameterization
7. Need to use tools able to derive **symbolic backpropagation**, even for fancy DAG-like networks possible
8. To read more: [M. Nielsen's Neural Networks and Deep Learning](#) online book