# On PDE approach to some machine learning problems

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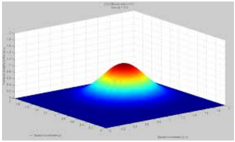
Partial differential equations (PDEs) are used to describe many phenomenons. Many famous PDEs are from physics.

- Heat: heat equation, $u$ tempature

$$\partial_t u = \sum_{i=1}^{3} \frac{\partial^2 u}{\partial x_i^2} = \Delta u$$



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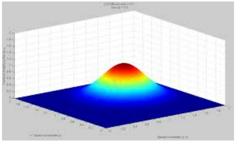

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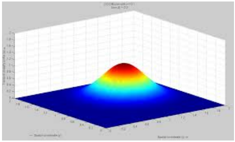

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- Quantum mechanics, electrodynamics, image processing,. . . .

# Probability and PDEs

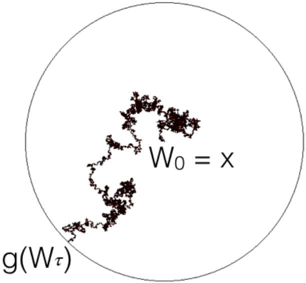


Figure: Brownian Motion

$W_t$: a Brownian motion with $W_0 = x$. $W$ hits boundary at $W_\tau$. $u(x) = \mathbb{E}^x[g(W_\tau)]$. Then

$$\Delta u = 0,$$

and

$$u = g \quad \text{on} \quad S_1.$$

# Online Learning: Examples


Figure: Spam Detection

- emails arrive one by one

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  - distribution fixed over time (training and test)
  - i.i.d. assumptions
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  - distribution fixed over time (training and test)
  - i.i.d. assumptions
  - a fixed predictor
- Online learning:
  - no distribution assumption
  - suitable for changing or adversarial environment
  - a natural model for many applications, mixing training and test
  - memory efficient

# Prediction With Expert Advices

- Need: to make a decision every day
  - which stock to invest in
  - which route to drive home
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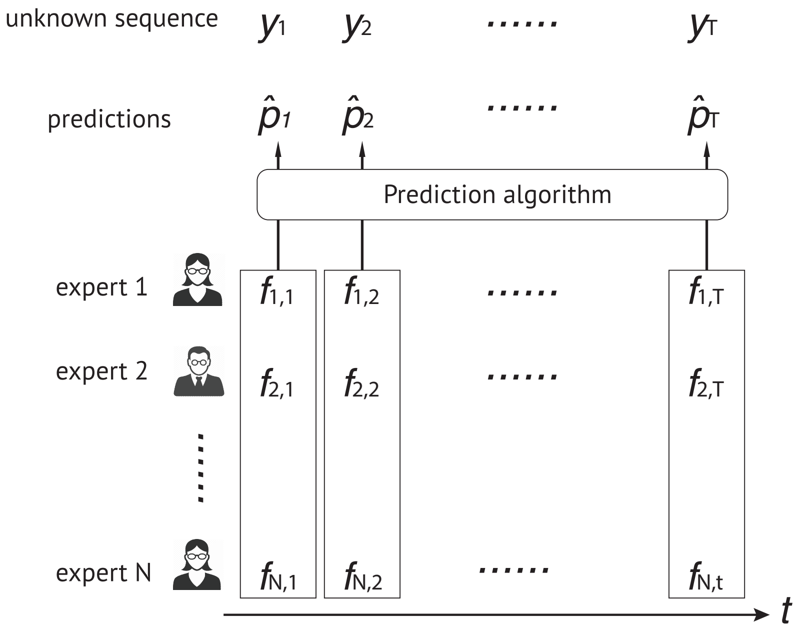
- Question: <u>How to combine advice and make smart choices?</u>


unknown sequence
y1
y2
......
yT
predictions
p̂1
p̂2
......
p̂T
Prediction algorithm
expert 1
expert 2
expert N
f1,1
f1,2
......
f1,T
f2,1
f2,2
......
f2,T
fN,1
fN,2
......
fN,t
t

# Gentle Start: a simple example

- Set up:
  - Predict an unknown sequence $y_1, y_2, \ldots,$ where $y_i \in \{0, 1\}$.
  - $N$ experts provide advice $(f_{1,t}, f_{2,t}, \ldots, f_{N,t})$
  - A forecaster makes her guess $\hat{p}_t \in \{0, 1\}$ for $y_t$
  - True $y_t$ is revealed and find if $\hat{p}_t = y_t$.
  - Know that one of the experts makes no mistakes.
- Goal: bound the number of the mistakes made by the forescaster

# Halving Algorithm

**Algorithm:**

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**Conclusion**: the number of mistakes made by the forecaster is bounded by $\lfloor \log_2 N \rfloor$.

# Proof

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- When the forecaster make her $m$th mistakes, at least half of the experts have been always correct make their first mistake

$$w_m \leq \frac{w_{m-1}}{2} \Longrightarrow w_m \leq \frac{w_0}{2^m}.$$

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- $w_i = 1$ for some $i$

$$m \leq \lfloor \log_2 N \rfloor.$$

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- Theorem: let $m_i^t$ be the number of mistakes made by expert $i$ till time $t$ and $m^t$ be the number of mistakes made by the WM algorithm. Then

$$m_t \leq \frac{\log_2 N + m_i^t \log_2 \frac{1}{\beta}}{\log_2 \frac{2}{1+\beta}}.$$

  - $m_t \leq O(\log_2 N) + \text{constant} \times \text{best expert}.$

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# General Setting

- For $t = 1$ to $T$ do
  - receive instance $x_t \in X$ and advice $\hat{y}_{t,i} \in Y$, $i \in [1, N]$
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- Objective: minimize regret, i.e., difference of total loss incurred and that of best exeprt:

$$Regret(T) = \sum_{t=1}^{T} L(y_t, \hat{y}_t) - \min_{i \in [1,N]} \sum_{t=1}^{T} L(y_t, \hat{y}_{t,i}).$$

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- Goal: obtain sublinear regret to the best expert. (top 10 experts, any competitor, etc. )

$$\lim_{T \to \infty} \frac{Regret(T)}{T} = 0.$$

# An Optimal Bound

- Exponential weighted average
  - weight update:
$$w_i^{t+1} \leftarrow w_i^t e^{-\eta_t L_{t,i}},$$
    where $L_{t,i}$ is total loss incurred by expert $i$ till time $t$
  - prediction:
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  - prediction:
  $$\hat{y}_t = \frac{\sum_{i=1}^N w_i^t y_{t,i}}{\sum_{i=1}^N w_i^t}.$$
- Theorem: Assume $L$ is convex in its first argument and takes values in $[0,1]$. Then for any $T$

$$Regret(T) \le \frac{\sqrt{2}}{\sqrt{2}-1}\sqrt{(T/2)\log_2 N} + \sqrt{\log_2 N/2}.$$

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- The bound can be improved if more information is known, e.g., if the loss functions are special, $L_2$ loss, $L_1$ loss,
- In general, the bound is asymptotically optimal.

# Active research area: literatures

- Littlestone and Warmuth develop weighted majority algorithm
- Cesa-Bianchi et al. obtain minimax regret bounded by $\sqrt{(T/2)\log N}$.
- Cesa-Bianchi and Lugosi connected the regret with the Rademacher Complexity of the set of experts.
- Even-Dar et al. considered regret to the average
- Rakhlin et al. developed Sequential Rademacher Complexity to study online learning.
- ...

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- Two naive experts: one always predicts 1 (always goes up); the other one always predicts -1(always goes down).

Cover proved

$$Regret(T) = \Theta(\sqrt{T}).$$

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- Typical Goal: minimize the worst-case regret with respect to the best performing expert.
- More general goal: minimize the worst case value of

  $\phi$(regret with respect to expert "1", regret with respect to expert "-1")

  at time $T$. ("Typical goal" is $\phi(x_1, x_2) = \max\{x_1, x_2\}$.)

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- value function: $v(x, t) =$ optimal time $T$ result, starting from relative regrets $x = (x_1, x_2)$ at time $t$.

Dynamical programming principle:

$$\begin{aligned} v(x_1, x_2, t) &= \min_{|p| \le 1} \max_{b = \pm 1} v(\text{new position}, t+1) \\ &= \min_{|p| \le 1} \max_{b = \pm 1} v(x_1 + b(1-p), x_2 - b(1+p), t+1) \end{aligned}$$

for $t < T$, with final-time condition $v(x, T) = \phi(x)$.

# Dynamical Programming Principle

Recall: $(x_1, x_2) =$ (regret w.r.t. "'1" expert, regret w.r.t. "-1" expert), where regret = (investor's loss) - (expert's loss).

If the investor buys $p$ shares and the market goes up, investor loss $-p$, the "+" expert loss $-1$, the "-1" expert loss 1. So the state moves from $(x_1, x_2)$ to $(x_1 - (1-p), x_2 + (1+p))$.

Similarly, if investor buys $p$ shares and market goes down, state move from $(x_1, x_2)$ to $(x_1 + (1-p), x_2 - (1+p))$.

Hence the dynamical programming principle:

$$v(x_1, x_2, t) = \min_{|p| \leq 1} \max_{b = \pm 1} v(x_1 + b(1-p), x_2 - b(1+p), t+1).$$

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- To access this question, it is natural to rescale the problem and look for a continuum limit.
- Our scaling is like the passage from random walk to Brownian motion.
  - Let $\xi_1, \xi_2, \ldots$ be i.i.d. random variable with mean 0 and variance 1. For each $n$, define a continuous-time stochastic processes $\{W_n(t)\}$

$$W_n(t) = \frac{1}{\sqrt{n}} \sum_{1 \le j \le [nt]} \xi_j.$$

Then $W_n(t) \to W_t$, where $W_t$ is a standard Brownian motion.

- So we consider a scaled version of the problem: stock moves $\pm\epsilon$, time steps are $\epsilon^2$, and the scaling of regret is $\epsilon^2$. The value function is still the optimal time-T result. The dynamical programming principle becomes

$$w^{\epsilon}(x_1, x_2, t) = \min_{|p|\leq 1} \max_{b=\pm 1} w^{\epsilon}(x_1 + \epsilon b(1-p), x_2 - \epsilon b(1+p), t + \epsilon^2)$$

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- We expect as $\epsilon \to 0$, $w^\epsilon(x,t) \to w(x,t)$ and $w$ solves some PDEs.

The partial differential equation is the Hamilton-Jacobi-Bellman equation associate with the optimal control problem. Formal derivation

1. Use the Taylor's expansion to estimate

$$w(x_1 + \epsilon b(1-p), x_2 - \epsilon(1+p), t + \epsilon^2).$$

2. Investor choose $p$ to make $O(\epsilon)$ terms vanishes; this gives

$$p = \frac{\partial_1 w - \partial_2 w}{\partial_1 w + \partial_2 w}.(\text{optimal strategy})$$

3. The $O(\epsilon^2)$ are insensitive to $b = \pm 1$; they give the nonlinear PDE

$$w_t + 2 < D^2 w \frac{\nabla^\perp w}{\partial_1 w + \partial_2 w}, \frac{\nabla^\perp w}{\partial_1 w + \partial_2 w} >= 0,$$

where $\nabla^\perp w = (\partial_2 w, -\partial_1 w)$. Prescribe the final value $w = \phi$ at $T$.

# Conclusion

- if $\phi$ smooth

$$\|w^{\epsilon}(x,t) - w(x,t)\| \leq C\epsilon,$$

  where $C$ independent of $t$.

- if $\phi(x) = \max\{x_1, x_2\}$

$$\|w^{\epsilon}(x,t) - w(x,t)\| \leq C\epsilon \log \epsilon.$$

- Equation can be solved explicitly.

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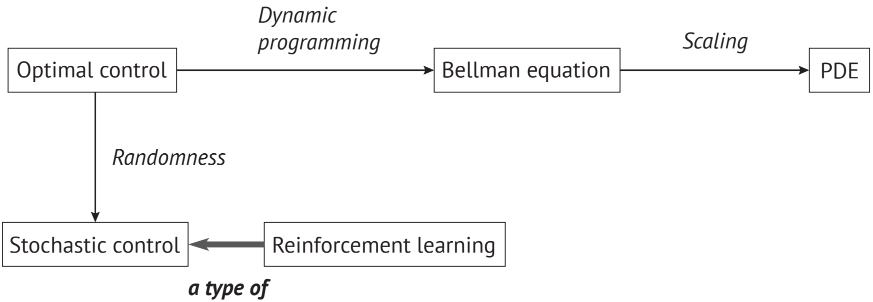
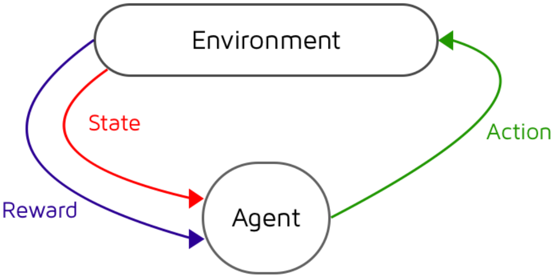
- Problem is considered as a deterministic two-person game.
- One can consider more complex situation, e.g., more experts, more intelligent experts, etc.
- Dynamical programming principle can be hard to derive.


Dynamic programming
Scaling
Optimal control
Bellman equation
PDE
Randomness
Stochastic control
Reinforcement learning
a type of

# Reinforcement Learning




S: Set of states

A: Set of actions

R: Reward function. $\forall s_t, a_t,\ r_t = R(s_t, a_t) \in \mathbb{R}$

- Markov decision process (MDP) is a discrete time stochastic control process. The value function $v : S \to \mathbb{R}$ satisfies a discrete Bellman equation.

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  - Given a policy $\pi$ with infinite horizon for any state $x \in X$

$$V_\pi(x) = R(x, \pi(x)) + \gamma \sum_{x' \in X} P(x'|x, \pi(x)) V_\pi(x')$$

  - Optimal policy

$$V^*(x) = \max_{a \in A} \{R(x, a) + \gamma \sum_{x' \in X} P(x'|x, a) V_\pi(x')\}$$

- Continuous time and state: PDEs.
  - Dynamics of the state

$$dX_s = b(X_s, a_s)\, ds + \sigma(X_s, a_s)\, dW_s, \tag{1}$$

where $W_s$ is Brownian motion and $a_s$ is control process.

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$$R(t, x, a) = \mathbb{E}\Big[\int_t^T f(X_s^{t,x}, a_s)\,ds + g(X_T^{t,x})\Big],$$

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    where $X^{t,x}$ is the solution of (1) starting from $X_t = x$.
  - Value function

$$v(t, x) = \sup_{a \in \mathcal{A}} R(t, x, a).$$

  - HJB equation

$$\frac{\partial v}{\partial t} + \sup_{a \in \mathcal{A}} \big(L_a v + f(x, a)\big) = 0 \quad \text{in} [0, T] \times \mathbb{R}^d,$$

    where $L_a$ is the infinitesimal generator of the process (1).

# Second-order Linear Elliptic PDEs

A classical example is

$$\Delta u(x) = \sum_{i=1}^{d} \frac{\partial^2 u}{\partial x_i^2} = 0.$$

Let $W_t$ be a Brownian motion starting from $x$. Then

$$\lim_{t \to 0} \frac{E^x u(W_t) - u(x)}{t} = \frac{1}{2} \Delta u.$$

General diffusion process

$$L_a u = \frac{1}{2} Tr(\sigma \sigma^T D^2 u) = \frac{1}{2} \sum_{i,j=1}^{d} a_{ij} D_{ij} u,$$

where $\{a_{ij}\}$ is some positive-definite matrix.

# HJB equation

Fully nonlinear equation ($v$ depends on $(t, x)$)

$$\partial_t v + \sup_{a \in \mathcal{A}} (L_a v + f(x, a)) = 0,$$

where $L_a$ is a second-order linear elliptic operator.

After deriving the HJB equation formally, the equation holds in a weak sense. The regularity of the solution is very low.

- Easy to find solution in the space of continuous function
- Equation holds in a very weak sense (viscosity solution).
- Important problem in the PDE community to prove the existence of classical solution.

# Mathematical Result

Recall:

$$dX_s = b(X_s, a_s)\, ds + \sigma(X_s, a_s)\, dW_s.$$

Under some regularity assumption on the coefficients $\sigma$, $b$, then the solution to the HJB

$$\partial_t u + \sup_{a \in \mathcal{A}} \big( L_a u + f(x, a) \big) = 0,$$

is a classical solution. Rigorously, $u \in C^{2,\alpha}$ for some $\alpha > 0$.

The theoretical results helps to build numerical scheme to solve the HJB.

# Jump processes and Nonlocal equations

Brownian motion is a continuous stochastic process. Consider more general process: Lévy processes (jump processes)

$$dX_s = b(X_s, a_s)\, ds + \sigma(X_s, a_s)\, dY_s,$$

where $Y_s$ is a Lévy process. The infinitesimal generator of such processes is nonlocal

$$L_a u = \int_{\mathbb{R}^d} (u(x+y) + u(x-y) - 2u(x)) \frac{K_a(y)}{|y|^{d+\sigma}}\, dy,$$

and $\sigma \in (0, 2)$.

**Theorem**

*Let $v$ be a weak solution to*

$$v_t + \sup_a (L_a v + f_a) = 0,$$

*where $L_a$ is a nonlocal operator defined previously. Then the solution $v$ is a classical solution and derivatives of $v$ are bounded.*

Thank you.