Experimentation in trading

For: Robo-Advisors & Systematic Investing / Vasant Dhar

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Introductions

- Me
  - Quant trader
  - Market making, stocks
  - Experimental optimization
- You
  - Studying
  - Trading
  - Modeling
  - Backtesting

Quant trading

Execution

- Agency: no position risk
- Big customer order ===> many small trades
- Thousands of trades / day

Quant trading

High-frequency market making (HFMM)

- Principal: Small positions for minutes
- Continuous quoting
- Thousands of trades / day

Quant trading

Statistical arbitrage

- Principal: Larger positions for hours to many days
- Opportunistic trade selection
- Tens - hundreds of trades / day

Experimentation

- Compare performance in **live trading**
- Returns predictions incomplete
  - risk, liquidity, capital, preferences
- Simulation (aka backtest) too hard
  - Market reaction / impact
  - Latencies
  - Complexity

Experimentation: Complexity

- Example: US stock market
  - 13 lit exchanges
  - “around 50” dark pools [https://www.marketswiki.com/wiki/Dark_pool]
  - continuous book, auctions, blind bidding, block trading, internalization
  - orders: limit, market, IOC, FOK, AON, ISO, hide & slide, hidden, post-only

Experimental methods

- Experimental methods b/c
  - Evaluation is expensive: $$/time/risk
  - Evaluation is uncertain (noisy)
- Experimental methods
  - Minimize expense
  - Minimize uncertainty

Experimental methods

- Without experimental method
  - Deploy new model, make money
  - ==> “My new model is great!”
- With experimental method
  - Run new and old models side-by-side
  - P{new beats old} = .53, deltaPnL = $700 ± $2200
  - ==> “My new model isn’t *bad*.”

Make better decisions

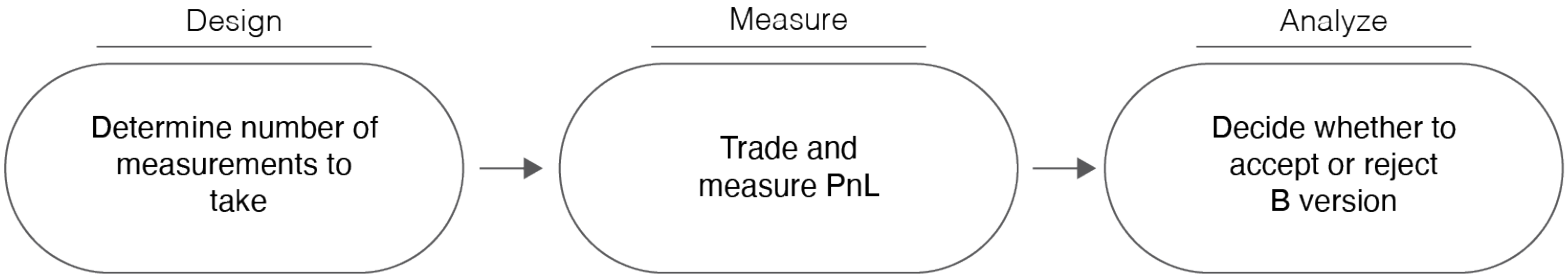
Experimentation pervasive

- Medicine
- Psychology
- Behavioral Economics
- Web search
- Online advertising
- Social media
- Food engineering
- Materials science
- Social science
- Manufacturing
- Consumer product design

Example: HFMM A/B test

- Scenario: HTF strategy
  - A: Existing model, across 100 stocks
  - B: Your new model
- Model B looks better than Model A
  - Lower out-of-sample RMSE
  - Higher PnL in simulations
- Next: A/B test in live trading

Example: HFMM A/B test



Example: HFMM A/B test

- Design:
  - Which stocks will run Model A, Model B?
  - How many days will this run?
- Measure:
  - Trade and record pnl by stock, day: $p_{s,d}$
- Analyze:
  - Which is better A or B?
  - Significantly better?

Design: Randomization

- Randomly assign 50 stocks to Model B, $\chi_B = 1$
- Assign other 50 to Model A, $\chi_B = 0$
- Experiment measures $corr(p_{s,d}, \chi_B)$

Design: Randomization

- Correlation w/anything else is confounder bias
  - Ex: All tech stocks in A, all energy stocks in B
  - Ex: High-liquidity stocks in A, low-liquidity stocks in B
  - Ex: …
- Randomization removes* confounder bias
  - *Even if you don't know the confounders*

*"removes" == "aims to minimize"

Design: Replication

- PnL is noisy
- Replication: Avg. over multiple days

$$\mu = \frac{\Sigma_d p_d}{N} \qquad se = \frac{\sqrt{\Sigma_d (p_d - \mu_d)^2}}{N} = \frac{\sigma}{\sqrt{N}}$$

- Replication decreases “noise” as $1/\sqrt{N}$

Design: Replication

- Before experiment
    1. Estimate se ← Data
    2. Specify minimum interesting δ_{min} ← Subjective
    3. Calculate N

Design: Find N

- Some analysis:
    - Limit false positives (5%)
    - Limit false negatives (20%)

$$N >= \left(\frac{2.8se}{\delta_{min}}\right)^2$$

NB: Quadratic

- Typically 1-2 weeks for real experiments

Measure

- Trade!
- Start small for safety
- Stop if *any* metrics look very bad / different
    - PnL terrible — or wonderful!
    - Trading way too little / too much
    - Sending too many / too few orders
- Log everything, record $p_{s,d}$

Analyze

- Which model earned more PnL?

$$\Delta_{PnL} = \mu_B - \mu_A$$

- Enough to care?

$$\Delta_{PnL} > \delta_{min}$$

- Statistically significantly more?

$$t = \frac{\Delta_{PnL}}{se_{PnL}} > 1.64$$

Measure: Warning

- Plan: Wait N days, then ask "Is $t > 1.64$?"

- Why not just check every day?
  - Stop when $t > 1.64$? ← Don't do this!
  - Many false positives!
- You can monitor t — Just don't stop based on t

Bayesian optimization

- Modern, flexible, efficient method(s)
- A.K.A.
  - Adaptive experimentation
  - Black box optimization
  - Surrogate optimization
  - Model-based optimization

Bayesian optimization

- Can compare A, B
- Also: A, B, C, D, …
- Also: 1, 2, 3, …
- Also: $[0,1]$, $[0,1]^D$
- Also: $\{A, B, C, \ldots\} \otimes \{a, b, c, \ldots\} \otimes \{1,2,3,...\} \otimes [0,1]^D$

- IOW: BO can optimize your strategy's parameters.

Bayesian optimization

- Other uses:
  - Hyperparameter optimization (HPO) for supervised learning models
    - NNs, trees
  - Optimize parameters of strategy in simulation
- BO takes longer to calculate a design …
  - Compared to, ex., BFGS, CMA-ES
- … but requires fewer experiments overall

Bayesian optimization: Design

- Fit a *surrogate*:

Analyzing, really

$$y(x) = \text{PnL(parameters)}$$

- Usually Gaussian process regression (GPR)

- Then, maximize $y(x)$ over x:

$$x = \underset{x}{\operatorname{argmax}}\, E[f(x)]$$

- **BUT**: Surrogate is poor b/c so few measurements

Bayesian optimization: Design

- Instead:

$$x = \underset{x}{\operatorname{argmax}}[\overbrace{\mathrm{E}[f(x)]}^{\text{Exploitation}} + \overbrace{\sqrt{\mathrm{VAR}[f(x)]}}^{\text{Exploration}}]$$

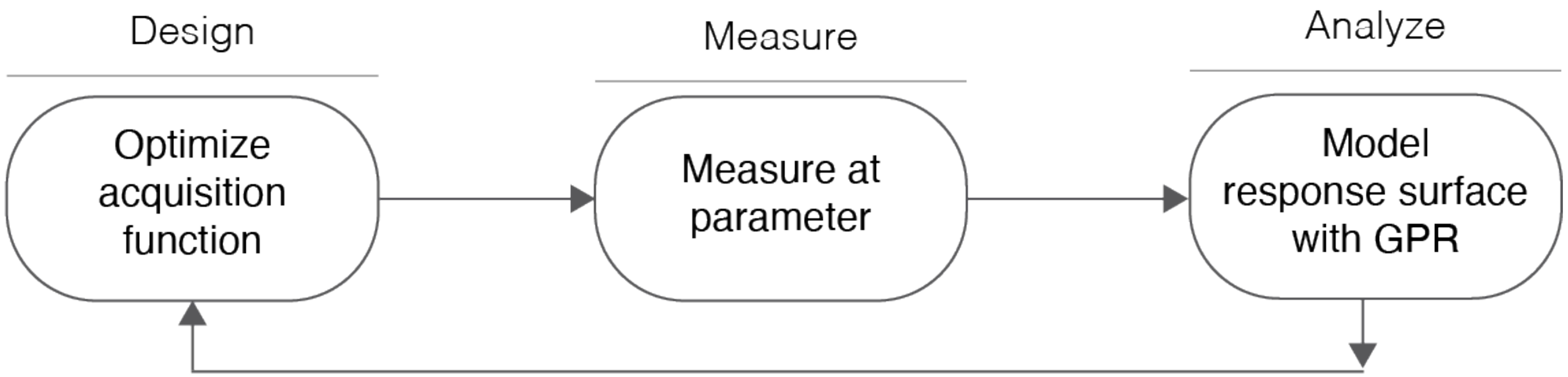
- GPR outputs $\mathrm{E}[f(x)]$ *and* $\mathrm{VAR}[f(x)]$
- *Acquisition function*: $\mathrm{E}[f(x)] + \sqrt{\mathrm{VAR}[f(x)]}$
- Exploration improves surrogate

Bayesian optimization: Measurement

- Same as before
- Go trade

Bayesian optimization: Analysis

- Have you exhausted your budget for experimentation?
- If not, rebuild GPR, design again



Bayesian optimization

- **Mixed variable types**: Continuous, ordinal (integer), and categorical (boolean)
- **Multiple metrics**: PnL, risk, volume, order rate, … simultaneously
- **Multiple fidelities**: Combine simulator results w/live results
- **Constraints**: Limit risk, capital, market participation
- **Arbitrary measurements**: Build surrogate from all available measurements

- You build your surrogate as a model of your whole trade.

Bayesian optimization: Tools

- Open source: botorch.org
    - SKLearn:Supervised learning :: BoTorch:Bayesian optimization
    - Flexible, powerful modeling toolkit
- cogneato.xyz
    - user-friendly
    - works with a spreadsheet or Pandas
    - simple, but produces good designs

Bayesian optimization: Summary

- Surrogate models trade
- Acquisition optimization designs experiments
- Iterate until done