The 7 Reasons Most Machine Learning Funds Fail

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Key Points

- Over the past 20 years, I have seen many new faces arrive to the financial industry, only to leave shortly after.
- The rate of failure is particularly high in machine learning (ML).
- In my experience, the reasons boil down to 7 common errors:
  1. The Sisyphus paradigm
  2. Integer differentiation
  3. Inefficient sampling
  4. Wrong labeling
  5. Weighting of non-IID samples
  6. Cross-validation leakage
  7. Backtest overfitting

- The contents of this presentation are based on my recent book: ***Advances in Financial Machine Learning***, Wiley (2018)

Pitfall #1:
The Sisyphean Quants

The silo approach works for discretionary PMs

- Discretionary portfolio managers (PMs) make investment decisions that do not follow a particular theory or rigorous rationale.
- Because nobody fully understands the logic behind their bets, they can hardly work as a team and develop deeper insights beyond the initial intuition.
- If 50 PMs tried to work together, they would influence each other until eventually 49 would follow the lead of 1.

For this reason, investment firms ask discretionary PMs to work in silos.

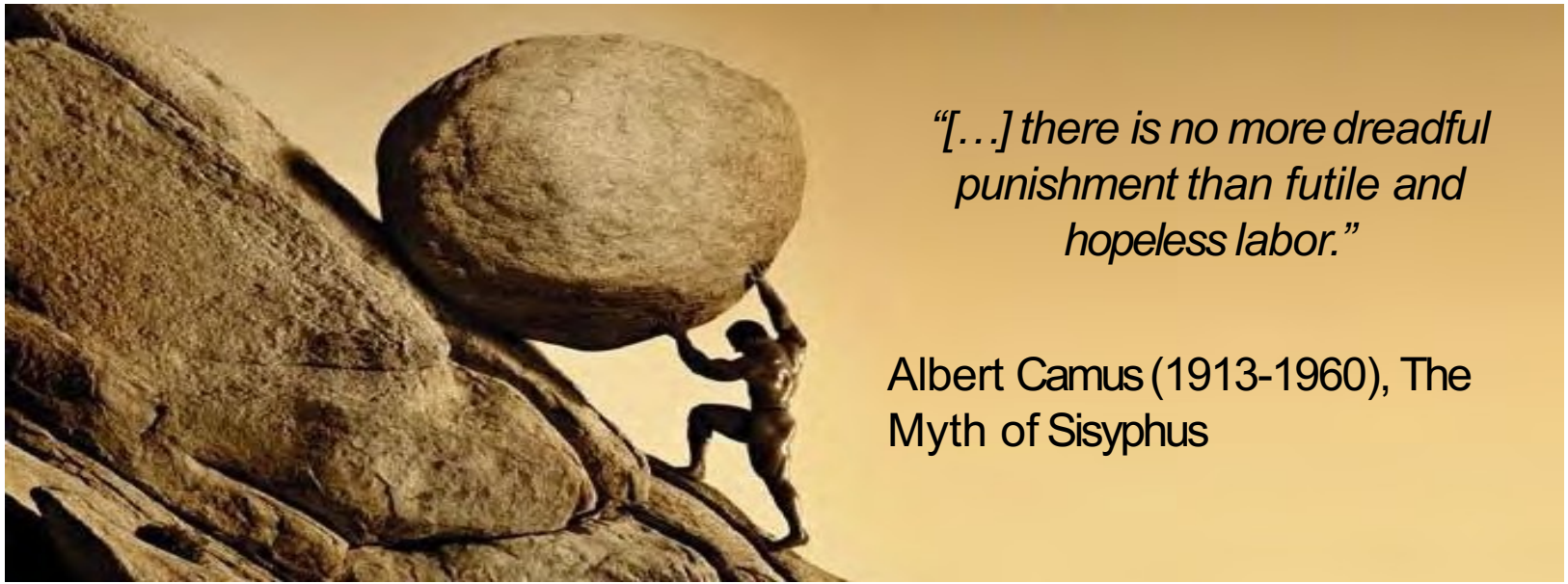
Silos prevent one PM from influencing the rest, hence protecting diversification.

The silo approach fails with quant PMs

- The boardroom's mentality is, let us do with quants what has worked with discretionary PMs.
- Let us hire 50 PhDs, and demand from each of them to produce an investment strategy within 6 months.
- This approach typically backfires, because each of these PhDs will frantically search for investment opportunities and eventually settle for:
  - A false positive that looks great in an overfit backtest; or
  - A standard factor model, which is an overcrowded strategy with low Sharpe ratio, but at least has academic support.
- Both outcomes will disappoint the investment board, and the project will be cancelled.
- Even if 5 of those 50 PhDs found something, they would quit.

Sisyphean Quants

- Firms directing quants to work in silos, or to develop individual strategies, are asking the impossible.
- Identifying new strategies requires large teams working together.



The Meta-Strategy Paradigm (1/3)

- The complexities involved in developing a true investment strategy are overwhelming:
  - Data collection, curation, processing, structuring,
  - HPC infrastructure,
  - software development,
  - feature analysis,
  - execution simulators,
  - backtesting, etc.
- Even if the firm provides you with shared services in those areas, you are like a worker at a BMW factory who has been asked to build the entire car alone, by using all the workshops around you.
  - One week you need to be a master welder, another week an electrician, another week a mechanical engineer, another week a painter, ... try, fail and circle back to welding. It is a futile endeavor.

The Meta-Strategy Paradigm (2/3)

- It takes almost as much effort to produce one true investment strategy as to produce a hundred.
- Every successful quantitative firm I am aware of applies the meta-strategy paradigm.
- Your firm must set up a research factory
  - where tasks of the assembly line are clearly divided into subtasks.
  - where quality is independently measured and monitored for each subtask.
  - where the role of each quant is to specialize in a particular subtask, to become the best there is at it, while having a holistic view of the entire process.
- This is how Berkeley Lab and other U.S. National laboratories routinely make scientific discoveries, such as adding 16 elements to the periodic table, or laying out the groundwork for MRIs and PET scans: https://youtu.be/G5nK3B5uuY8

The Meta-Strategy Paradigm (3/3)

Practical Application	Classic approach	Quantitative Meta-Strategy
Selection & Hiring (Example 1)	Interview candidates with SR (or any other performance statistic) and track record length above a given threshold. Pros: Trivial to implement. Cons: Unknown (possibly high) probability of hiring unskilled PMs.	Design an interview process that recognizes the variables that affect the probability of making the wrong hire: • False positive rate. • False negative rate. • Skill-to-unskilled odds ratio. • Number of independent trials. • Sampling mechanism. Pros: It is objective and can be improved over time, based on measurable outcomes. Cons: More laborious.
Oversight (Example 2)	Allocate capital as if PMs were asset classes. Pros: Trivial to implement. Cons: Correlations are unstable, meaningless. Risks are likely to be concentrated.	Recognize that PMs styles evolve over time, as they adapt to a changing environment. Pros: It provides an early signal while the style is still emerging. Allocations can be revised before it is too late. Cons: Allocation revisions may be needed on an irregular calendar frequency.
Stop-Out (Example 3)	Stop-out a PM once a certain loss limit has been exceeded. Pros: Trivial to implement. Cons: It allows preventable problems to grow until it is too late.	For any drawdown, large or small, determine the expected time underwater and monitor every recovery. Even if a loss is small, a failure to recover within the expected timeframe indicates a latent problem. Pros: Proactive. Address problems before they force a stop-out. Cons: PMs may feel under tighter scrutiny.

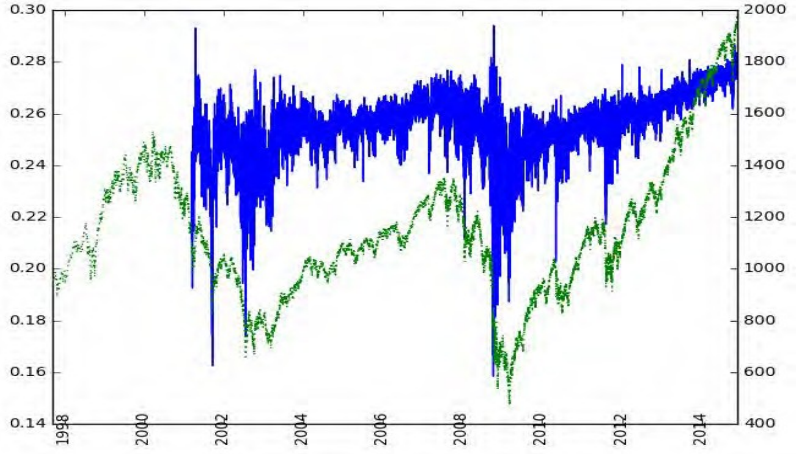
Pitfall #2:
Integer Differentiation

The Stationarity vs. Memory Dilemma

- In order to perform inferential analyses, researchers need to work with invariant processes, such as
  - returns on prices (or changes in log-prices)
  - changes in yield
  - changes in volatility
- These operations make the series stationary, at the expense of removing all memory from the original series.
- Memory is the basis for the model's predictive power.
  - For example, equilibrium (stationary) models need some memory to assess how far the price process has drifted away from the long-term expected value in order to generate a forecast.
- The dilemma is
  - returns are stationary however memory-less; and
  - prices have memory however they are non-stationary.

The Optimal Stationary-Memory Trade Off

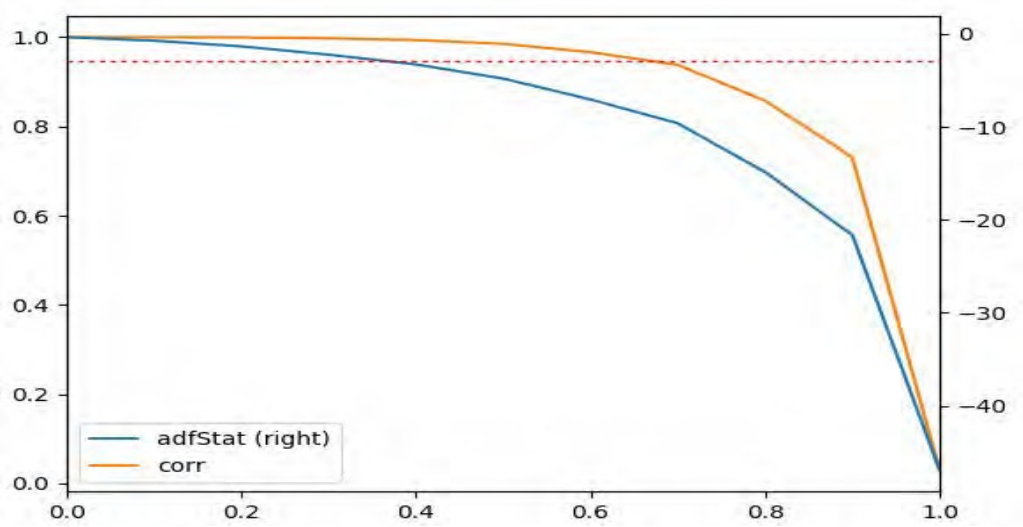
- Question: What is the minimum amount of differentiation that makes a price series stationary while preserving as much memory as possible?
- Answer: We would like to generalize the notion of returns to consider stationary series where not all memory is erased.
- Under this framework, returns are just one kind of (and in most cases suboptimal) price transformation among many other possible.



- Green line: E-mini S&P 500 futures trade bars of size 1E4
- Blue line: Fractionally differentiated (d= .4)
- Over a short time span, it resembles returns
- Over a longer time span, it resembles price levels

Example 1: E-mini S&P 500 Futures

- On the x-axis, the *d* value used to generate the series on which the ADF stat was computed.
- On the left y-axis, the correlation between the original series ($d = 0$) and the differentiated series at various *d* values.
- On the right y-axis, ADF stats computed on log prices.



The original series ($d = 0$) has an ADF stat of -0.3387, while the returns series ($d = 1$) has an ADF stat of -46.9114.

At a 95% confidence level, the test's critical value is -2.8623.

The ADF stat crosses that threshold in the vicinity of $d = 0.35$, where correlation is still very high (0.995).

Example 2: Optimal FradDiff Stationarity (1/2)

	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
AD1 Curncy	-1.7253	-1.8665	-2.2801	-2.9743	-3.9590	-5.4450	-7.7387	-10.3412	-15.7255	-22.5170	-43.8281
BO1 Comdty	-0.7039	-1.0021	-1.5848	-2.4038	-3.4284	-4.8916	-7.0604	-9.5089	-14.4065	-20.4393	-38.0683
BP1 Curncy	-1.0573	-1.4963	-2.3223	-3.4641	-4.8976	-6.9157	-9.8833	-13.1575	-19.4238	-26.6320	-43.3284
BTS1 Comdty	-1.7987	-2.1428	-2.7600	-3.7019	-4.8522	-6.2412	-7.8115	-9.4645	-11.0334	-12.4470	-13.6410
BZ1 Index	-1.6569	-1.8766	-2.3948	-3.2145	-4.2821	-5.9431	-8.3329	-10.9046	-15.7006	-20.7224	-29.9510
C 1 Comdty	-1.7870	-2.1273	-2.9539	-4.1642	-5.7307	-7.9577	-11.1798	-14.6946	-20.9925	-27.6602	-39.3576
CC1 Comdty	-2.3743	-2.9503	-4.1694	-5.8997	-8.0868	-10.9871	-14.8206	-18.6154	-24.1738	-29.0285	-34.8580
CD1 Curncy	-1.6304	-2.0557	-2.7284	-3.8380	-5.2341	-7.3172	-10.3738	-13.8263	-20.2897	-27.6242	-43.6794
CF1 Index	-1.5539	-1.9387	-2.7421	-3.9235	-5.5085	-7.7585	-11.0571	-14.6829	-21.4877	-28.9810	-44.5059
CL1 Comdty	-0.3795	-0.7164	-1.3359	-2.2018	-3.2603	-4.7499	-6.9504	-9.4531	-14.4936	-20.8392	-41.1169
CN1 Comdty	-0.8798	-0.8711	-1.1020	-1.4626	-1.9732	-2.7508	-3.9217	-5.2944	-8.4257	-12.7300	-42.1411
CO1 Comdty	-0.5124	-0.8468	-1.4247	-2.2402	-3.2566	-4.7022	-6.8601	-9.2836	-14.1511	-20.2313	-39.2207
CT1 Comdty	-1.7604	-2.0728	-2.7529	-3.7853	-5.1397	-7.1123	-10.0137	-13.1851	-19.0603	-25.4513	-37.5703
DM1 Index	-0.1929	-0.5718	-1.2414	-2.1127	-3.1765	-4.6695	-6.8852	-9.4219	-14.6726	-21.5411	-49.2663
DU1 Comdty	-0.3365	-0.4572	-0.7647	-1.1447	-1.6132	-2.2759	-3.3389	-4.5689	-7.2101	-10.9025	-42.9012
DX1 Curncy	-1.5768	-1.9458	-2.7358	-3.8423	-5.3101	-7.3507	-10.3569	-13.6451	-19.5832	-25.8907	-37.2623
EC1 Comdty	-0.2727	-0.6650	-1.3359	-2.2112	-3.3112	-4.8320	-7.0777	-9.6299	-14.8258	-21.4634	-44.6452
EC1 Curncy	-1.4733	-1.9344	-2.8507	-4.1588	-5.8240	-8.1834	-11.6278	-15.4095	-22.4317	-30.1482	-45.6373
ED1 Comdty	-0.4084	-0.5350	-0.7948	-1.1772	-1.6633	-2.3818	-3.4601	-4.7041	-7.4373	-11.3175	-46.4487
EE1 Curncy	-1.2100	-1.6378	-2.4216	-3.5470	-4.9821	-7.0166	-9.9962	-13.2920	-19.5047	-26.5158	-41.4672
EO1 Comdty	-0.7903	-0.8917	-1.0551	-1.3465	-1.7302	-2.3500	-3.3068	-4.5136	-7.0157	-10.6463	-45.2100
EO1 Index	-0.6561	-1.0567	-1.7409	-2.6774	-3.8543	-5.5096	-7.9133	-10.5674	-15.6442	-21.3066	-35.1397
ER1 Comdty	-0.1970	-0.3442	-0.6334	-1.0363	-1.5327	-2.2378	-3.2819	-4.4647	-7.1031	-10.7389	-40.0407
ES1 Index	-0.3387	-0.7206	-1.3324	-2.2252	-3.2733	-4.7976	-7.0436	-9.6095	-14.8624	-21.6177	-46.9114
FA1 Index	-0.5292	-0.8526	-1.4250	-2.2359	-3.2500	-4.6902	-6.8272	-9.2410	-14.1664	-20.3733	-41.9705
FC1 Comdty	-1.8846	-2.1853	-2.8808	-3.8546	-5.1483	-7.0226	-9.6889	-12.5679	-17.8160	-23.0530	-31.6503
FV1 Comdty	-0.7257	-0.8515	-1.0596	-1.4304	-1.8312	-2.5302	-3.6296	-4.9499	-7.8292	-12.0467	-49.1508
G 1 Comdty	0.2326	0.0026	-0.4686	-1.0590	-1.7453	-2.6761	-4.0336	-5.5624	-8.8575	-13.3277	-42.9177
GC1 Comdty	-2.2221	-2.3544	-2.7467	-3.4140	-4.4861	-6.0632	-8.4803	-11.2152	-16.7111	-23.1750	-39.0715
GX1 Index	-1.5418	-1.7749	-2.4666	-3.4417	-4.7321	-6.6155	-9.3667	-12.5240	-18.6291	-25.8116	-43.3610
HG1 Comdty	-1.7372	-2.1495	-2.8323	-3.9090	-5.3257	-7.3805	-10.4121	-13.7669	-19.8902	-26.5819	-39.3267
HI1 Index	-1.8289	-2.0432	-2.6203	-3.5233	-4.7514	-6.5743	-9.2733	-12.3722	-18.5308	-25.9762	-45.3396
HO1 Comdty	-1.6024	-1.9941	-2.6619	-3.7131	-5.1772	-7.2468	-10.3326	-13.6745	-19.9728	-26.9772	-40.9824
IB1 Index	-2.3912	-2.8254	-3.5813	-4.8774	-6.5884	-9.0665	-12.7381	-16.6706	-23.6752	-30.7986	-43.0687
IK1 Comdty	-1.7373	-2.3000	-2.7764	-3.7101	-4.8686	-6.3504	-8.2195	-9.8636	-11.7882	-13.3983	-14.8391
IR1 Comdty	-2.0622	-2.4188	-3.1736	-4.3178	-5.8119	-7.9816	-11.2102	-14.7956	-21.6158	-29.4555	-46.2683
JA1 Comdty	-2.4701	-2.7292	-3.3925	-4.4658	-5.9236	-8.0270	-11.2082	-14.7198	-21.2681	-28.4380	-42.1937
JB1 Comdty	-0.2081	-0.4319	-0.8490	-1.4289	-2.1160	-3.0932	-4.5740	-6.3061	-9.9454	-15.0151	-47.6037
JE1 Curncy	-0.9268	-1.2078	-1.7565	-2.5398	-3.5545	-5.0270	-7.2096	-9.6808	-14.6271	-20.7168	-37.6954
JG1 Comdty	-1.7468	-1.8071	-2.0654	-2.5447	-3.2237	-4.3418	-6.0690	-8.0537	-12.3908	-18.1881	-44.2884
JO1 Comdty	-3.0052	-3.3099	-4.2639	-5.7291	-7.5686	-10.1683	-13.7068	-17.3054	-22.7853	-27.7011	-33.4658
JY1 Curncy	-1.2616	-1.5891	-2.2042	-3.1407	-4.3715	-6.1600	-8.8261	-11.8449	-17.8275	-25.0700	-44.8394
KC1 Comdty	-0.7786	-1.1172	-1.7723	-2.7185	-3.8875	-5.5651	-8.0217	-10.7422	-15.9423	-21.8651	-35.3354
L 1 Comdty	-0.0805	-0.2228	-0.6144	-1.0751	-1.6335	-2.4186	-3.5676	-4.8749	-7.7528	-11.7669	-44.0349

These tables show ADF stats for the most liquid futures contracts worldwide.

One row per instrument, and one column per differentiation value.

Highlighted in green are ADF values that do not reject the null hypothesis of unit root.

Highlighted in red are ADF values that reject the null hypothesis of unit root.

Example 2: Optimal FradDiff Stationarity (2/2)

	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
LB1 Comdty	-2.0133	-2.2043	-2.7692	-3.7363	-4.9980	-6.8712	-9.5572	-12.5024	-17.7300	-23.1173	-31.9508
LC1 Comdty	-3.0977	-3.2487	-4.0104	-5.1441	-6.8472	-9.1425	-12.4560	-16.0186	-21.8070	-27.1929	-34.2574
LH1 Comdty	-2.4059	-2.5980	-2.6847	-3.0616	-3.7269	-4.8461	-6.6899	-8.8143	-13.3179	-18.6747	-34.4944
MFS1 Index	-1.8618	-2.4061	-3.0316	-4.2111	-5.6544	-8.2728	-11.3954	-14.2083	-19.2276	-23.7318	-29.9174
NG1 Comdty	-1.2022	-1.2278	-1.2971	-1.5259	-1.9188	-2.5619	-3.5688	-4.7757	-7.4392	-11.2455	-41.3164
NI1 Index	-1.0865	-1.4354	-2.1171	-3.0946	-4.3528	-6.1476	-8.8056	-11.7667	-17.6428	-24.6738	-43.8325
NK1 Index	-0.8467	-1.1964	-1.8390	-2.7349	-3.8871	-5.5119	-7.9025	-10.5570	-15.8085	-22.0688	-38.7505
NQ1 Index	0.0153	-0.2883	-0.7985	-1.5227	-2.3900	-3.5965	-5.3719	-7.4372	-11.7580	-17.5718	-47.7300
NX1 Index	-1.2749	-1.6410	-2.3648	-3.4331	-4.8169	-6.8106	-9.7514	-13.0195	-19.3190	-26.5442	-43.2635
O 1 Comdty	-1.9643	-2.3536	-3.1711	-4.4057	-6.0102	-8.3139	-11.6484	-15.2893	-21.7540	-28.5592	-39.9112
OAT1 Comdty	-2.1234	-1.9151	-2.2928	-2.9948	-3.9627	-5.3126	-7.0749	-8.8556	-11.2388	-13.2080	-15.0069
OE1 Comdty	0.1688	-0.0863	-0.4587	-0.8500	-1.3174	-2.0411	-2.9760	-4.0461	-6.4504	-9.8420	-44.0898
PA1 Comdty	-1.4237	-1.6949	-2.2550	-3.1287	-4.2748	-5.9456	-8.4346	-11.2251	-16.6076	-22.8823	-37.8283
PE1 Curncy	-1.7713	-2.1928	-3.0869	-4.3894	-6.0523	-8.4218	-11.9137	-15.7241	-22.6601	-30.1037	-43.8788
PT1 Index	-1.9088	-2.2753	-3.0047	-4.1548	-5.6979	-7.9456	-11.2588	-14.8504	-21.5933	-28.9158	-43.4395
QS1 Comdty	-0.2084	-0.4919	-0.9675	-1.6192	-2.4490	-3.6160	-5.3075	-7.2161	-11.0838	-15.9596	-32.1660
RR1 Comdty	-0.0657	-0.4432	-0.9827	-1.6856	-2.5403	-3.7445	-5.4592	-7.4618	-11.4360	-16.4247	-33.0067
RTA1 Index	-0.4991	-0.8450	-1.4518	-2.2701	-3.3347	-4.8131	-7.0163	-9.4859	-14.4313	-20.5139	-38.4632
RX1 Comdty	0.3374	0.0368	-0.3370	-0.8033	-1.3293	-2.0307	-3.1201	-4.2717	-6.8379	-10.4035	-43.1525
S 1 Comdty	-2.3905	-2.5632	-3.0364	-3.8647	-5.0057	-6.7561	-9.4036	-12.4148	-18.2529	-24.9520	-39.1747
SB1 Comdty	-1.3895	-1.7489	-2.4806	-3.5180	-4.9204	-6.9044	-9.7911	-12.8777	-18.5958	-24.6554	-35.9220
SF1 Curncy	-2.4335	-2.8967	-3.8496	-5.3187	-7.2411	-9.9945	-13.9627	-18.2641	-25.8117	-33.5334	-46.1841
SI1 Comdty	-1.6435	-1.9468	-2.6104	-3.6207	-4.9544	-6.8834	-9.7471	-12.9306	-18.9448	-25.6872	-39.6744
SM1 Comdty	-2.1197	-2.0686	-2.2593	-2.7314	-3.5152	-4.6986	-6.5691	-8.7911	-13.3516	-19.1866	-37.8627
SM1 Index	-1.4716	-1.7336	-2.3942	-3.3732	-4.6921	-6.5834	-9.3968	-12.5018	-18.5601	-25.5175	-42.7253
SP1 Index	-0.5900	-0.9726	-1.6887	-2.6118	-3.7857	-5.4356	-7.8842	-10.6784	-16.4223	-23.8436	-50.2515
ST1 Index	-1.5957	-1.8926	-2.5130	-3.4803	-4.7593	-6.6294	-9.4127	-12.5153	-18.4786	-25.2546	-40.7900
TP1 Index	-1.2901	-1.6144	-2.2911	-3.3049	-4.5946	-6.4768	-9.2514	-12.3480	-18.5256	-25.9865	-46.2311
TU1 Comdty	-0.6340	-0.6768	-0.8529	-1.1306	-1.5256	-2.1951	-3.2065	-4.2674	-6.8060	-10.4758	-48.7361
TW1 Index	-1.1854	-1.5331	-2.2852	-3.3336	-4.6677	-6.5776	-9.3678	-12.4932	-18.5628	-25.6502	-42.5179
TY1 Comdty	-0.8208	-0.9876	-1.2585	-1.6069	-2.1026	-2.8142	-4.0467	-5.4328	-8.6137	-13.1678	-48.6412
UB1 Comdty	-0.3052	-0.5418	-0.9441	-1.4744	-2.1400	-3.0797	-4.4703	-6.0749	-9.4466	-13.9063	-36.3328
US1 Comdty	-0.8071	-1.1082	-1.5195	-2.0586	-2.8385	-4.0023	-5.7401	-7.7040	-12.0160	-18.0689	-47.9605
VG1 Index	-1.9920	-2.4127	-3.3269	-4.7189	-6.5700	-9.1847	-13.0116	-17.1131	-24.4105	-31.9086	-44.9058
VH1 Index	-1.5805	-1.9248	-2.7044	-3.8438	-5.3480	-7.5449	-10.7841	-14.3586	-21.2567	-29.0585	-46.5168
W 1 Comdty	-0.6236	-0.9148	-1.3959	-2.1267	-3.0507	-4.3849	-6.3497	-8.6538	-13.3216	-19.3053	-41.4181
XB1 Comdty	-2.2352	-2.4744	-2.9506	-3.7092	-4.9733	-6.7217	-9.4858	-12.5086	-18.3777	-25.0316	-39.5784
XG1 Comdty	-2.0082	-2.0972	-2.3756	-3.0026	-3.9027	-5.3023	-7.5000	-10.0158	-15.1353	-21.6376	-41.2603
XM1 Comdty	-0.9140	-1.1841	-1.8967	-2.8240	-4.0056	-5.6936	-8.2092	-11.0940	-17.0495	-24.7002	-51.5154
XP1 Index	-1.5053	-1.7699	-2.4437	-3.4436	-4.7258	-6.6019	-9.3891	-12.5294	-18.8368	-26.5249	-48.0102
YM1 Comdty	-1.1028	-1.1658	-1.6422	-2.3731	-3.3197	-4.6849	-6.7878	-9.1765	-14.2354	-20.9065	-49.2648
YS1 Comdty	-1.9101	-2.1735	-2.8727	-3.8500	-5.2679	-7.2488	-10.2821	-13.6430	-19.9992	-27.0788	-41.5913
Z 1 Index	-1.3096	-1.7242	-2.6045	-3.7736	-5.3196	-7.5241	-10.7341	-14.2851	-21.0992	-28.7746	-45.6802

Most financial series can be made stationary with a fractional differentiation of order $d < 0.5$.

However, most financial studies are based on returns, where $d = 1$.

The implication is that for decades most financial research has been based on **over-differentiated (memory-less) series**, leading to spurious forecasts and overfitting.

Pitfall #3:
Inefficient Sampling

Chronological Sampling

- Information does not arrive to the market at a constant entropy rate.
- Sampling data in chronological intervals means that the informational content of the individual observations is far from constant.
- A better approach is to sample observations as a subordinated process of the amount of information exchanged:
  - Trade bars.
  - Volume bars.
  - Dollar bars.
  - Volatility or runs bars.
  - Order imbalance bars.
  - Entropy bars.

Example 1: Dollar Bars (1/2)

- Let's define the imbalance at time T as $\theta_T = \sum_{t=1}^{T} b_t v_t$ where $b_t \in \{-1, 1\}$ is the aggressor flag, and v_t may represent either the number of securities traded or the dollar amount exchanged.
- We compute the expected value of θ_T at the beginning of the bar

$$E_0[\theta_T] = E_0\left[\sum_{t|b_t=1} v_t\right] - E_0\left[\sum_{t|b_t=-1} v_t\right]$$
$$= E_0[T](P[b_t = 1 | b_t = 1] - P[b_t = -1 | b_t = -1])$$

- Let's denote $v^+ = P[b_t = 1 | b_t = 1]$, $v^- = P[b_t = -1 | b_t = -1]$, so that $E_0[T]^{-1} E_0[v_t] = E_0[v_t] = v^+ + v^-$. You can think of v^+ and v^- as decomposing the initial expectation of v_t into the component contributed by buys and the component contributed by sells.

Example 1: Dollar Bars (2/2)

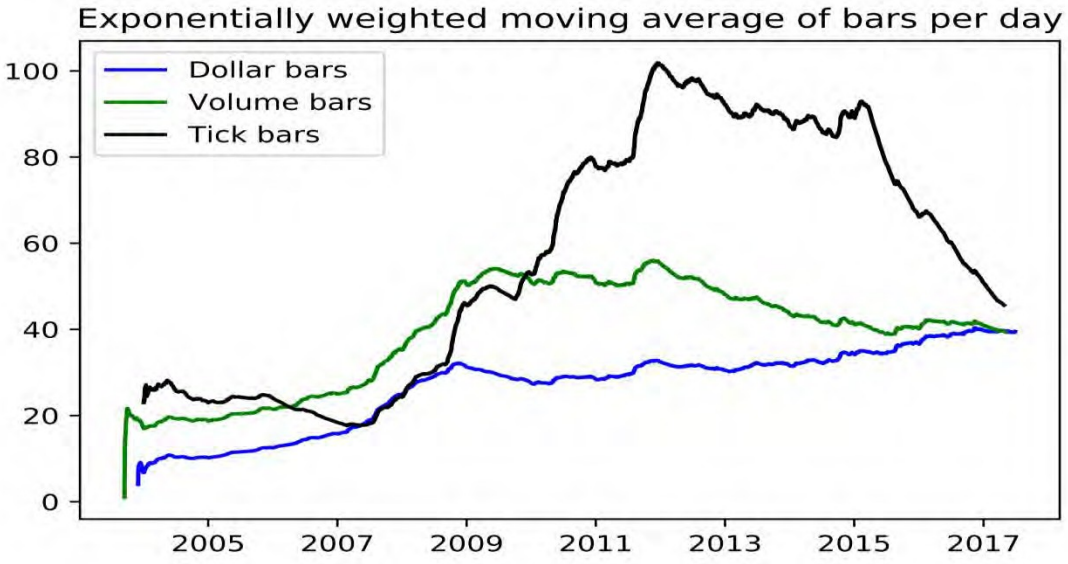
- Then, $E_0[\theta_T] = E_0[T](v^+ - v^-) = E_0[T](2v^+ - E_0[v_t])$
- In practice, we can estimate $E_0[T]$ as an exponentially weighted moving average of T values from prior bars, and $(2v^+ - E_0[v_t])$ as an exponentially weighted moving average of v_t values from prior bars.
- We define a bar as a T^*-contiguous subset of ticks such that the following condition is met

$$T^* = \underset{T}{\arg\min} \{|\theta_T| \geq E_0[T]|2v^+ - E_0[v_t]|\}$$

where the size of the expected imbalance is implied by $|2v^+ - E_0[v_t]|$.

- When θ_T is more imbalanced than expected, a low T will satisfy these conditions.

Example 2: Sampling Frequencies



Three bar types computed on E-mini S&P 500 futures.

Tick bars tend to exhibit a wide range of sampling frequencies, for multiple microstructural reasons.

Sampling frequencies for **volume bars** are often inversely proportional to price levels.

In general, **dollar bars** tend to exhibit more stable sampling frequencies.

Pitfall #4:
Wrong Labeling

Labeling in Finance

- Virtually all ML papers in finance label observations using the fixed-time horizon method.
- Consider a set of features $\{X_i\}_{i=1,\ldots,I}$, drawn from some bars with index $t = 1, \ldots, T$, where $I \leq T$. An observation X_t is assigned a label $y \in \{-1, 0, 1\}$,

$$y = \begin{cases} -1 & \text{if } r_{t_0,t_0+h} < -\tau \\ 0 & \text{if } |r_{t_0,t_0+h}| \leq \tau \\ 1 & \text{if } r_{t_0,t_0+h} > \tau \end{cases}$$

where τ is a pre-defined constant threshold, t_0 is the index of the bar immediately after X_t takes place, $t_0 + h$ is the index of h bars after t_0 and r_{t_0,t_0+h} is the price return over a bar horizon h.

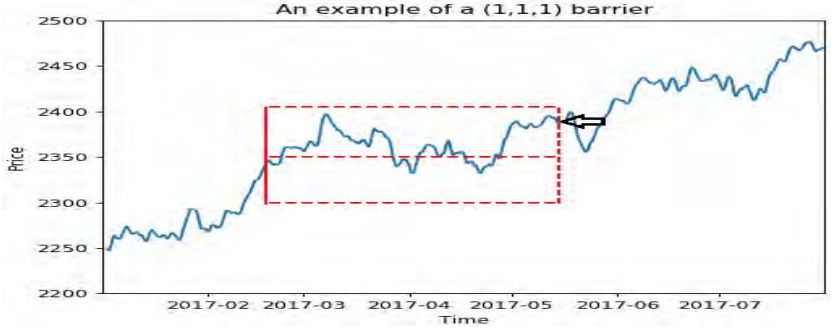
- Because the literature almost always works with time bars, h implies a fixed-time horizon.

Caveats of the Fixed Horizon Method

- There are several reasons to avoid such labeling approach:
  - Time bars do not exhibit good statistical properties.
  - The same threshold τ is applied regardless of the observed volatility.
    - Suppose that $\tau = 1E-2$, where sometimes we label an observation as $y = 1$ subject to a realized bar volatility of $\sigma_{t_0} = 1E-4$ (e.g., during the night session), and sometimes $\sigma_{t_0} = 1E-2$ (e.g., around the open). The large majority of labels will be 0, even if return r_{t_0,t_0+h} was predictable and statistically significant.
- A couple of better alternatives would be:
  - Label per a varying threshold σ_{t_0} estimated using a rolling exponentially-weighted standard deviation of returns.
  - Use volume or dollar bars, as their volatilities are much closer to constant (homoscedasticity).
- A key flaw of the fixed-time horizon method: It ignores the *path* followed by prices. We will address this with the Triple Barrier Method.

The Triple Barrier Method

- It is simply unrealistic to build a strategy that profits from positions that would have been stopped-out by the fund, exchange (margin call) or investor.
- The Triple Barrier Method labels an observation according to the first barrier touched out of three barriers.
  - Two horizontal barriers are defined by profit-taking and stop-loss limits, which are a dynamic function of estimated volatility (whether realized or implied).
  - A third, vertical barrier, is defined in terms of number of bars elapsed since the position was taken (an expiration limit).
- The barrier that is touched first by the *price path* determines the label:
  - Upper horizontal barrier: Label 1.
  - Lower horizontal barrier: Label -1.
  - Vertical barrier: Label 0.



How to use Meta-labeling

- Meta-labeling is particularly helpful when you want to achieve higher F1-scores:
  - First, we build a model that achieves high recall, even if the precision is not particularly high.
  - Second, we correct for the low precision by applying meta-labeling to the positives identified by the primary model.
- Meta-labeling is a very powerful tool in your arsenal, for three additional reasons:
  - ML algorithms are often criticized as black boxes. Meta-labeling allows you to build a ML system on a white box.
  - The effects of overfitting are limited when you apply meta-labeling, because ML will not decide the side of your bet, only the size.
  - Achieving high accuracy on small bets and low accuracy in large bets will ruin you. As important as identifying good opportunities is to size them properly, so it makes sense to develop a ML algorithm solely focused on getting that critical decision (sizing) right.

Meta-labeling for "Quantamental" Firms

- You can always add a meta-labeling layer to any primary model, whether that is an ML algorithm, a econometric equation, a technical trading rule, a fundamental analysis…
- That includes forecasts generated by a human, solely based on his intuition.
- In that case, meta-labeling will help us figure out when we should pursue or dismiss a discretionary PM's call.
- The features used by such meta-labeling ML algorithm could range from market information to biometric statistics to psychological assessments.
- Meta-labeling should become an essential ML technique for every discretionary hedge fund. In the near future, every discretionary hedge fund will become a quantamental firm, and meta-labeling offers them a clear path to make that transition.

Pitfall #5:
Weighting of non-IID samples

The "spilled samples" problem (1/2)

- Most non-financial ML researchers can assume that observations are drawn from IID processes. For example, you can obtain blood samples from a large number of patients, and measure their cholesterol.
- Of course, various underlying common factors will shift the mean and standard deviation of the cholesterol distribution, but the samples are still independent: There is one observation per subject.
- Suppose you take those blood samples, and someone in your laboratory spills blood from each tube to the following 9 tubes to their right.
  - That is, tube 10 contains blood for patient 10, but also blood from patients 1 to 9. Tube 11 contains blood from patient 11, but also blood from patients 2 to 10, and so on.

The "spilled samples" problem (2/2)

- Now you need to determine the features predictive of high cholesterol (diet, exercise, age, etc.), without knowing for sure the cholesterol level of each patient.
- That is the equivalent challenge that we face in financial ML.
  - Labels are decided by outcomes.
  - Outcomes are decided over multiple observations.
  - Because labels overlap in time, we cannot be certain about what observed features caused an effect.

My friend Luna can recognize faces, like Google or FaceBook. She is not so good at investing, and Google's ML would probably fail miserably if applied to financial markets.

Finance is not a plug-and-play subject as it relates to ML

Weighting observations by uniqueness (1/2)

- Two labels y_i and y_j are concurrent at t when both are a function of at least one common return, $r_{t-1,t} = \frac{p_t}{p_{t-1}} - 1$.

1. For each observation $t = 1, \ldots, T$ we form a binary array, $\{1_{t,i}\}_{i=1,\ldots,I}$, with $1_{t,i} \in \{0,1\}$, which indicates whether its outcome spans over return $r_{t-1,t}$.
2. We compute the number of labels concurrent at t, $c_t = \sum_{i=1}^{I} 1_{t,i}$.
3. The uniqueness of a label i at time t is $u_{t,i} = 1_{t,i} c_t^{-1}$.
4. The average uniqueness of label i is the average $u_{t,i}$ over the label's lifespan, $\bar{u}_i = \left(\sum_{t=1}^{T} u_{t,i} \right) \left(\sum_{t=1}^{T} 1_{t,i} \right)^{-1}$.

Weighting observations by uniqueness (2/2)

5. Sample weights can be defined in terms of the sum of the attributed returns over the event's lifespan, $[t_{i,0}, t_{i,1}]$

$$w_i = \left| \sum_{t=t_{i,0}}^{t_{i,1}} \frac{r_{t-1,t}}{c_t} \right|^{-1}$$

$$w_i = w_i \left(\sum_{j=1}^{I} w_j \right)^{-1}$$

- The rationale for this method is that we weight an observation as a function of the absolute log returns that can be attributed *uniquely* to it.

Pitfall #6:
Cross-Validation (CV) Leakage

Why standard CV fails in Finance

- One reason k-fold CV fails in finance is because observations cannot be assumed to be drawn from an IID process.
- *Leakage* takes place when the training set contains information that also appears in the testing set.
- Consider a serially correlated feature X that is associated with labels Y that are formed on overlapping data:
  - Because of the serial correlation, $X_t \approx X_{t+1}$.
  - Because labels are derived from overlapping data points, $Y_t \approx Y_{t+1}$.
- Then, placing t and $t+1$ in different sets leaks information.
  - When a classifier is first trained on (X_t, Y_t), and then it is asked to predict $E_{t+1}[Y_{t+1}]$ based on an observed X_{t+1}, this classifier is more likely to achieve $Y_{t+1} = E_{t+1}[Y_{t+1}]$ even if X_{t+1} is an irrelevant feature.
- In the presence of irrelevant features, leakage leads to false discoveries.

Purged K-Fold CV

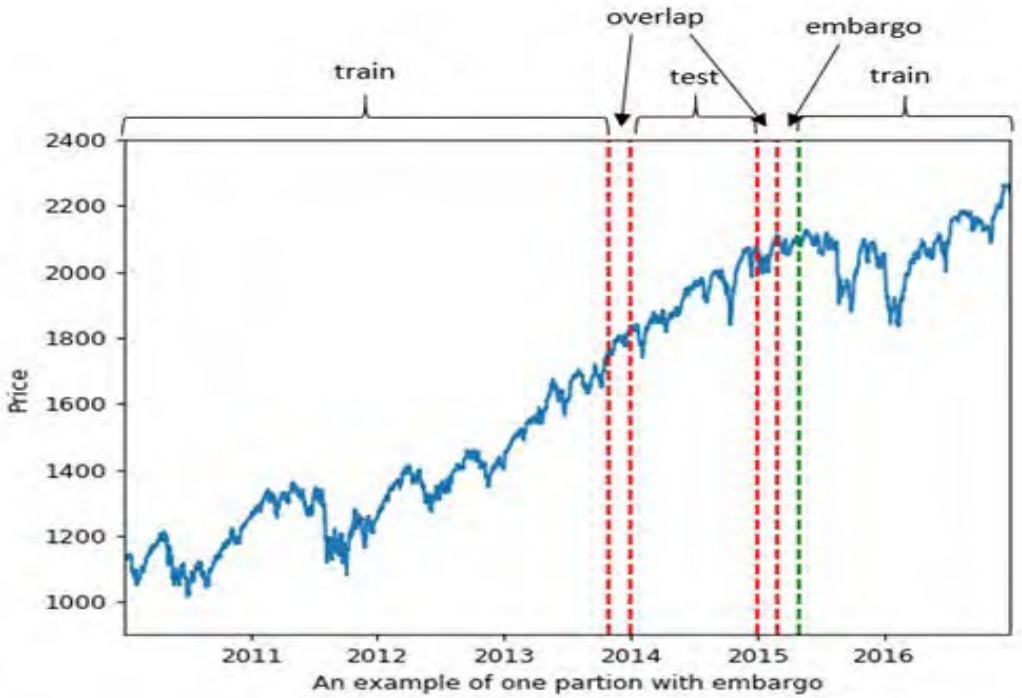
- One way to reduce leakage is to purge from the training set all observations whose labels overlapped in time with those labels included in the testing set. I call this process *purging*.
- Consider a label Y_j that is a function of observations in the closed range $t \in [t_0, t_1]$, $Y_j = f\left[[t_0, t_1]\right]$.
  - For example, in the context of the triple barrier labeling method, it means that the label is the sign of the return spanning between price bars with indices t_0 and t_1 that is $\text{sgn}\left[r_{t_0,t_1}\right]$.
- A label $Y_i = f\left[[t_{i,0}, t_{i,1}]\right]$ overlaps with Y_j if any of the three sufficient conditions is met:

$$t_{j,0} \leq t_{i,0} \leq t_{j,1} \quad t_{i,0} \leq t_{j,0} \leq t_{i,1} \quad t_{j,0} \leq t_{i,1} \leq t_{j,1}$$

Embargoed K-Fold CV

- Since financial features often incorporate series that exhibit serial correlation (like ARMA processes), we should eliminate from the training set observations that immediately follow an observation in the testing set. I call this process *embargo*.
  - The embargo does not need to affect training observations prior to a test, because training labels $Y_i = f\left[\left[t_{0,i}, t_{1,i}\right]\right]$, where $t_{1,i} < t_{0,j}$ (training ends before testing begins), contain information that was available at the testing time $t_{0,j}$
  - We are only concerned with training labels $Y_i = f\left[\left[t_{0,i}, t_{1,i}\right]\right]$ that take place immediately after the test, $t_{1,j} \leq t_{0,i} \leq t_{1,j} + h$.
- We can implement this embargo period h by setting $Y_j = f\left[\left[t_{0,j}, t_{1,j} + h\right]\right]$ before purging. A small value $h \approx .01T$, where T is the number of bars, often suffices to prevent all leakage.

Example: Purging and Embargoing

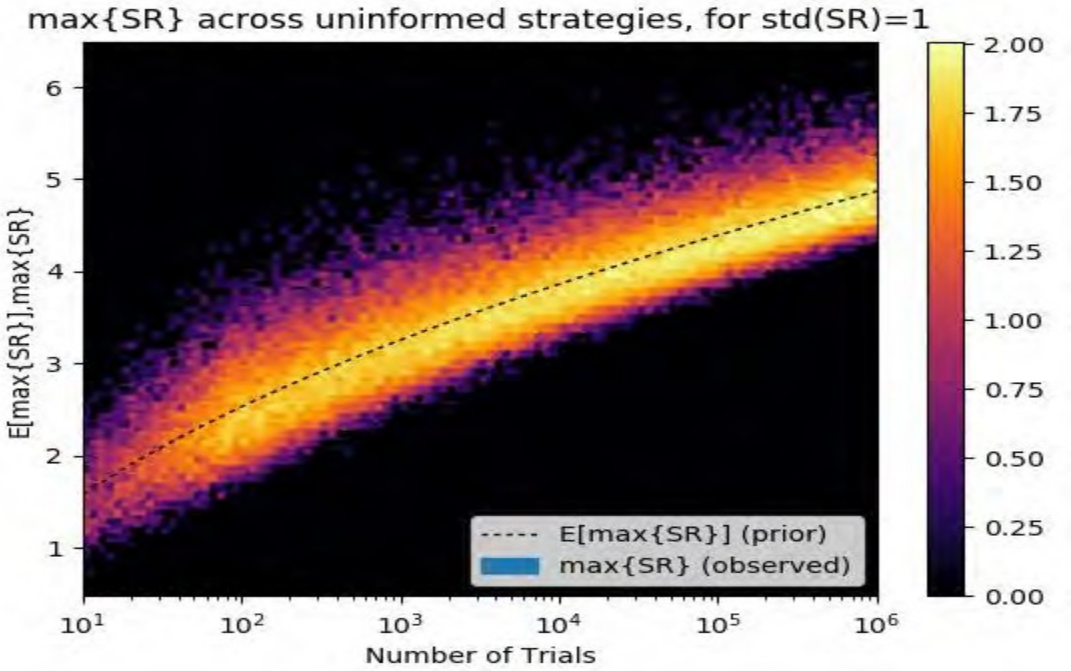


This plot shows one partition of the K-Fold CV. The test set is surrounded by two train sets, generating two overlaps that must be purged to prevent leakage.

To further prevent leakage, the train observations immediately after the testing set are also embargoed.

Pitfall #7:
Backtest Overfitting

The Most Important Plot In Finance



The y-axis displays the distribution of the maximum Sharpe ratios (max{SR}) for a given number of trials (x-axis). A lighter color indicates a higher probability of obtaining that result, and the dash-line indicates the expected value. For example, after only 1,000 independent backtests, the expected maximum Sharpe ratio (E[max{SR}]) is 3.26, even if the true Sharpe ratio of the strategy is zero!

The reason is *Backtest Overfitting*: When selection bias (picking the best result) takes place under multiple testing (running many alternative configurations), that backtest is likely to be a false discovery. **Most quantitative firms invest in false discoveries**.

The "False Strategy" Theorem [2014]

- Given a sample of IID-Gaussian Sharpe ratios, $\{SR_k, k = 1, \ldots, K\}$, with $SR_k \sim \mathcal{N}\left[0, V\left[\{SR_k\}\right]\right]$, then

$$E\left[\max_k \{SR_k\}\right] \left(V\left[\{SR_k\}\right]\right)^{-\frac{1}{2}} \approx (1 - \gamma)Z^{-1}\left[1 - \frac{1}{K}\right] + \gamma Z^{-1}\left[1 - \frac{1}{Ke}\right]$$

where $Z^{-1}[\,]$ is the inverse of the standard Gaussian CDF, e is Euler's number, and γ is the Euler-Mascheroni constant.

- Corollary: Unless $\max_k\{SR_k\} \gg E\left[\max_k \{SR_k\}\right]$, the discovered strategy is likely to be a *false positive*.

Source: López de Prado et al. (2014): "The effects of backtest overfitting on out-of-sample performance." *Notices of the American Mathematical Society*, 61(5), pp. 458-471.

The Deflated Sharpe Ratio (1/2)

- The Deflated Sharpe Ratio computes the probability that the Sharpe Ratio (SR) is statistically significant, after controlling for the inflationary effect of multiple trials, data dredging, non-normal returns and shorter sample lengths.

$$DSR \equiv \hat{PSR}(SR_0) = Z\left[\frac{(\widehat{SR} - SR_0)\sqrt{T-1}}{\sqrt{1 - \hat{\gamma}_3 \widehat{SR} + \frac{\hat{\gamma}_4 - 1}{4}\widehat{SR}^2}}\right]$$

where

$$SR_0 = \sqrt{V\left[\{\widehat{SR}_k\}\right]}\left((1-\gamma)Z^{-1}\left[1 - \frac{1}{K}\right] + \gamma Z^{-1}\left[1 - \frac{1}{Ke}\right]\right)$$

- DSR packs more information than SR, and it is expressed in probabilistic terms.

The Deflated Sharpe Ratio (2/2)

- The standard SR is computed as a function of two estimates:
  - Mean of returns
  - Standard deviation of returns.
- DSR deflates SR by taking into consideration five additional variables (it packs more information):
  - The non-Normality of the returns (γ_3, γ_4)
  - The length of the returns series (T)
  - The amount of data dredging ($V[\{SR_k\}]$)
  - The number of independent trials involved in the discovered strategy (K)

DSR can be used to determine the probability that a discovered strategy is a **False Positive**. The key is to record all trials, and determine correctly the number of effectively independent trials, *K*.
This will be the subject of my next paper, *Detection of False Strategies*. Stay tuned!

THANKS FOR YOUR ATTENTION!

Bio

Dr. Marcos López de Prado is the chief executive officer of *True Positive Technologies*. He founded *Guggenheim Partners*' Quantitative Investment Strategies (QIS) business, where he developed high-capacity machine learning (ML) strategies that consistently delivered superior risk-adjusted returns. After managing up to $13 billion in assets, Marcos acquired QIS and successfully spun-out that business from Guggenheim in 2018.

Since 2010, Marcos has been a research fellow at *Lawrence Berkeley National Laboratory* (U.S. Department of Energy, Office of Science). One of the top-10 most read authors in finance (SSRN's rankings), he has published dozens of scientific articles on ML and supercomputing in the leading academic journals, and he holds multiple international patent applications on algorithmic trading.

Marcos earned a PhD in Financial Economics (2003), a second PhD in Mathematical Finance (2011) from *Universidad Complutense de Madrid*, and is a recipient of Spain's National Award for Academic Excellence (1999). He completed his post-doctoral research at *Harvard University* and *Cornell University*, where he teaches a Financial ML course at the School of Engineering. Marcos has an Erdős #2 and an Einstein #4 according to the *American Mathematical Society*.

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