CEN 5016: Software Engineering

Spring 2024

University of Central Florida

Dr. Kevin Moran

Week 2 - Class 1: Measurement & Metrics

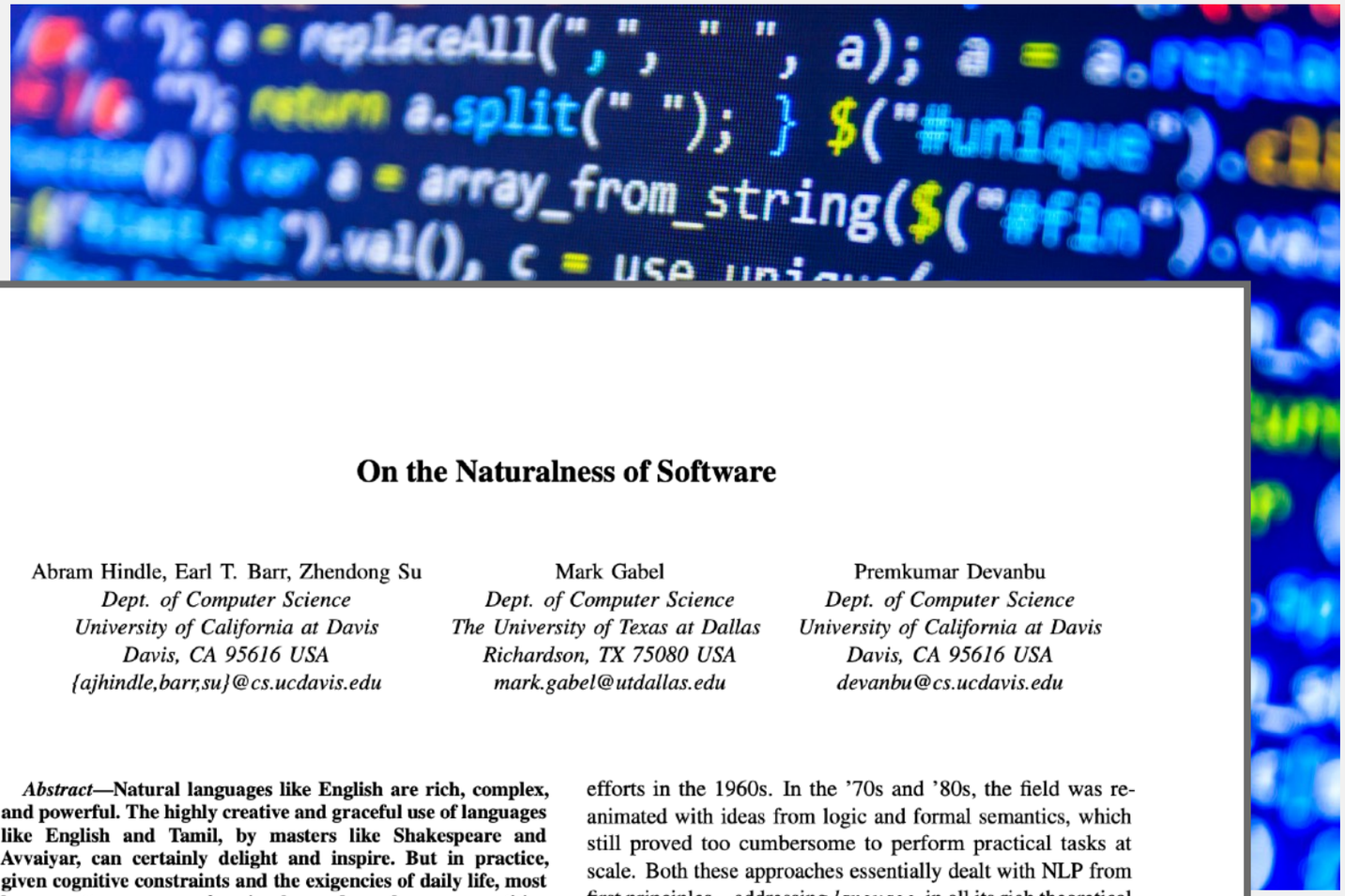
Administrivia

- Course Schedule Posted
- Office Hours Decided
  - Tuesday/Thursday 12:00pm-1:00pm (before class) Hybrid
  - Or by appointment
- Let me know if you are not on Ed Discussions
- Assignment 1, Getting started with Git, GitHub, and Typescript is due tonight at 11:59 pm
  - Use Megathread on Ed Discussions to ask questions
- Team-forming this week
  - Teams of 3 students
  - Look out for a post on Ed Discussions
- Assignment 2 out tomorrow

Software Archeology & Anthropology

Observation: Software is Full of Patterns

- File structure
- System architecture
- Code structure
- Names
- …



Check for updates

On the Naturalness of Software

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***Abstract*—Natural languages like English are rich, complex, and powerful. The highly creative and graceful use of languages like English and Tamil, by masters like Shakespeare and Avvaiyar, can certainly delight and inspire. But in practice, given cognitive constraints and the exigencies of daily life, most human utterances are far simpler and much more repetitive and predictable. In fact, these utterances can be very usefully modeled using modern statistical methods. This fact has led to the phenomenal success of statistical approaches to speech recognition, natural language translation, question-answering, and text mining and comprehension.**

We begin with the conjecture that most software is also natural, in the sense that it is created by humans at work, with all the attendant constraints and limitations—and thus, like natural language, it is also likely to be repetitive and predictable. We then proceed to ask whether a) code can be usefully modeled by statistical language models and b) such models can be leveraged to support software engineers. Using the widely adopted n-gram model, we provide empirical evidence supportive of a positive answer to both these questions. We show that code is also very repetitive, and in fact even more so than natural languages. As an example use of the model, we have developed a simple code completion engine for Java that, despite its simplicity, already improves Eclipse's built-in completion capability. We conclude the paper by laying out a vision for future research in this area.

***Keywords*-language models; n-gram; natural language processing; code completion; and code suggestion**

efforts in the 1960s. In the '70s and '80s, the field was reanimated with ideas from logic and formal semantics, which still proved too cumbersome to perform practical tasks at scale. Both these approaches essentially dealt with NLP from first principles—addressing *language*, in all its rich theoretical glory, rather than examining corpora of actual *utterances*, *i.e.*, what people actually write or say. In the 1980s, a fundamental shift to *corpus-based, statistically rigorous* methods occurred. The availability of large, on-line corpora of natural language text, including "aligned" text with translations in multiple languages,[1] along with the computational muscle (CPU speed, primary and secondary storage) to estimate robust statistical models over very large data sets has led to stunning progress and widely-available practical applications, such as statistical translation used by `translate.google.com`.[2] We argue that an essential fact underlying this modern, exciting phase of NLP is *natural language may be complex and admit a great wealth of expression, but what people write and say is largely regular and predictable.*

Our *central hypothesis* is that the same argument applies to software:

> *Programming languages, in theory, are complex,*

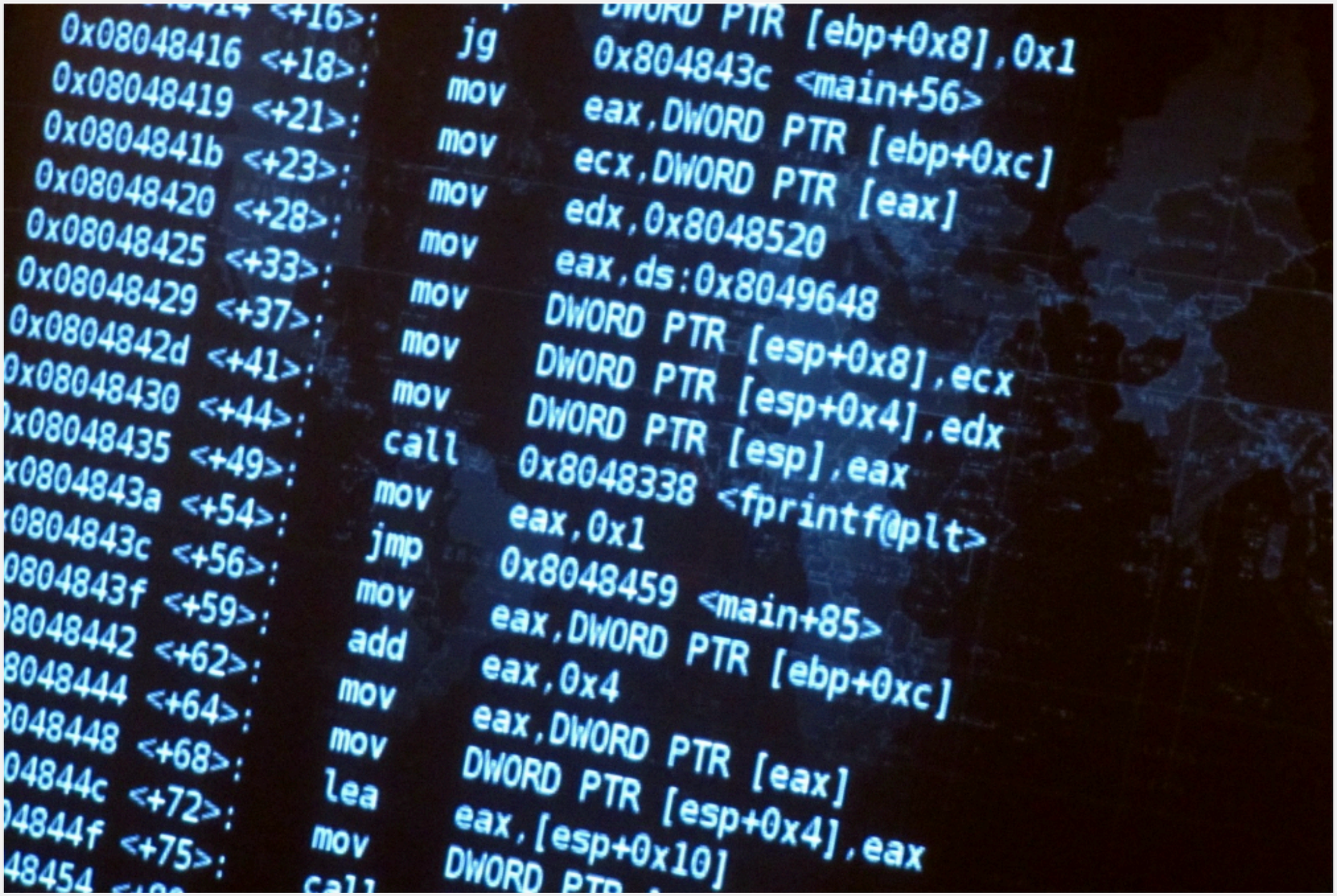
Observation: Software is Massively Redundant

- There is always something to copy/use as a starting point!

Observation: Code Must Run to Do Stuff!

Observation: If Code Runs, it Must have a Beginning…

Observation: If Code Runs, it Must Exist



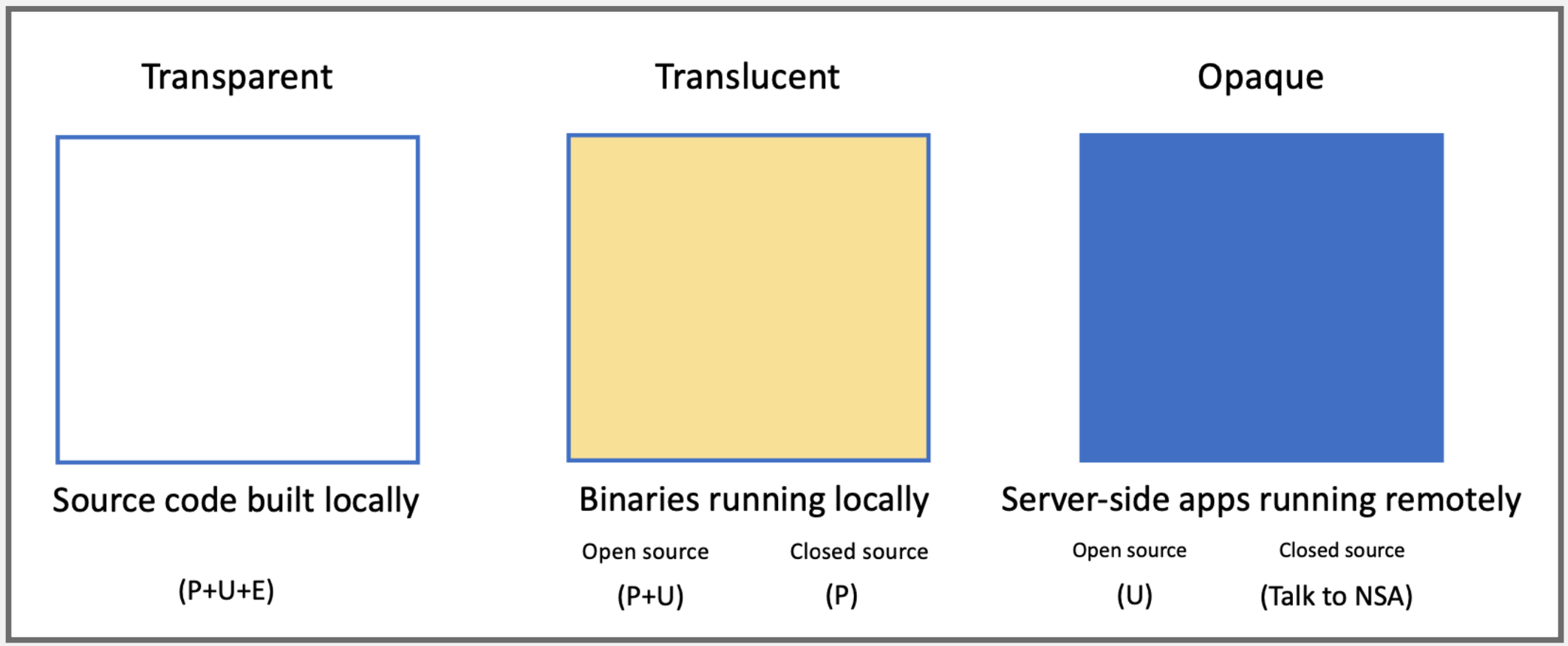
The Beginning: Entry Points

- Locally installed programs: run cmd, OS launch, I/O events, etc.
- Local applications in dev: build + run, test, deploy (e.g., docker)
- Web apps server-side: Browser sends HTTP request (GET/POST)
- Web apps client-side: Browser runs JavaScript, event handlers

Code Must Exist: But Where?

- Locally installed programs: run cmd, OS launch, I/O events, etc.
  - Binaries (machine code) on your computer
- Local applications in dev: build + run, test, deploy (e.g., docker)
  - Source code in repository (+ dependencies)
- Web apps server-side: Browser sends HTTP request (e.g., GET, POST)
  - Code runs remotely (you can only observe outputs)
- Web apps client-side: Browser runs JavaScript, event handlers
  - Source code is downloaded and run locally (see: browser dev tools!)

Can Running Code be Probed/Understood/Edited?



Creating a Model of Unfamiliar Code

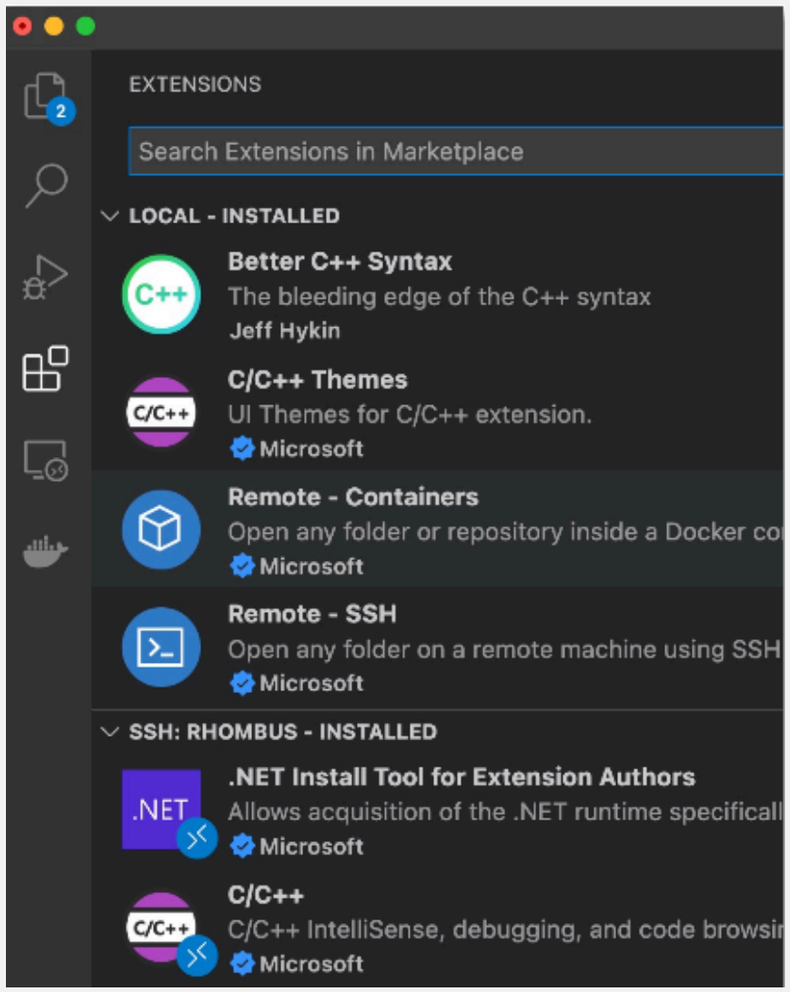
Information Gathering

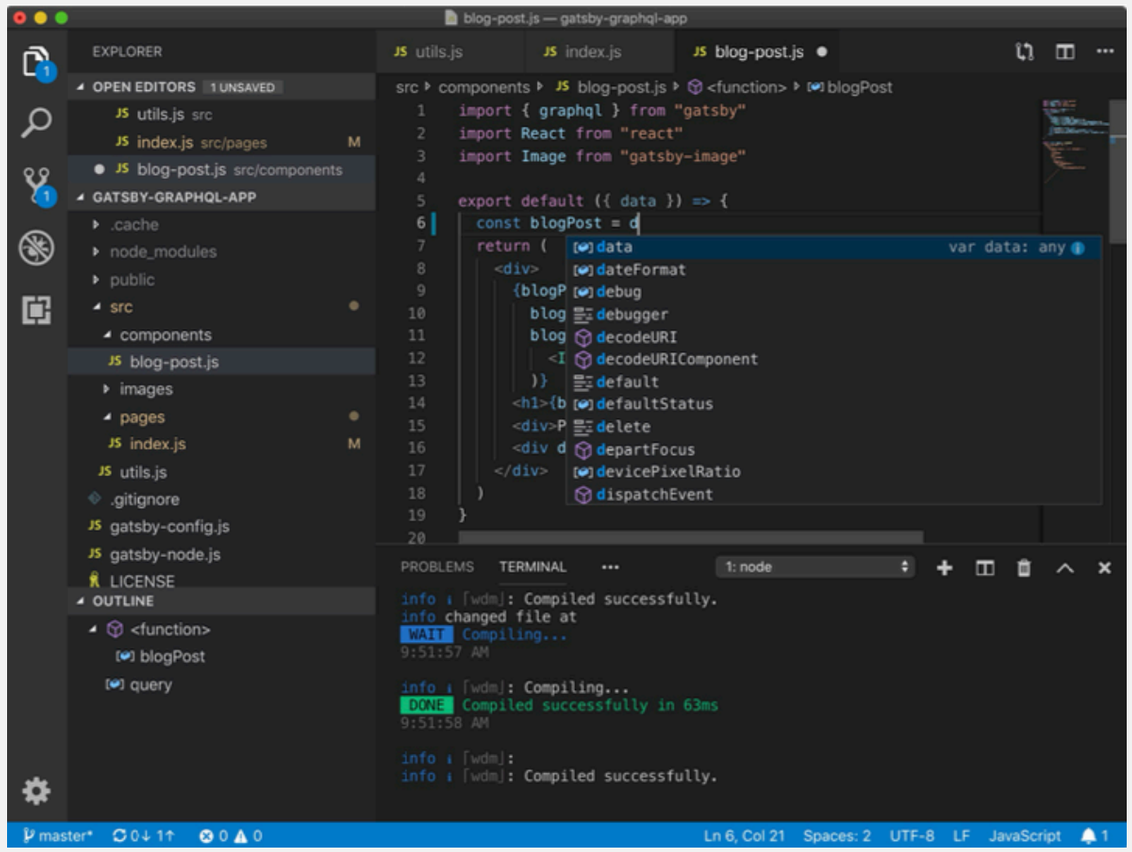
- Basic needs:
  - Code/file search and navigation
  - Code editing (probes)
  - Execution of code, tests
  - Observation of output (observation)

- At the command line: grep and find! (Google for tutorials)

- Many choices here on tools! Depends on circumstance.
  - grep/find/etc.
  - Knowing Unix tools is invaluable
  - A decent IDE
  - Debugger
  - Test frameworks + coverage reports
  - Google (or your favorite web search engine)
  - ChatGPT or LaMA

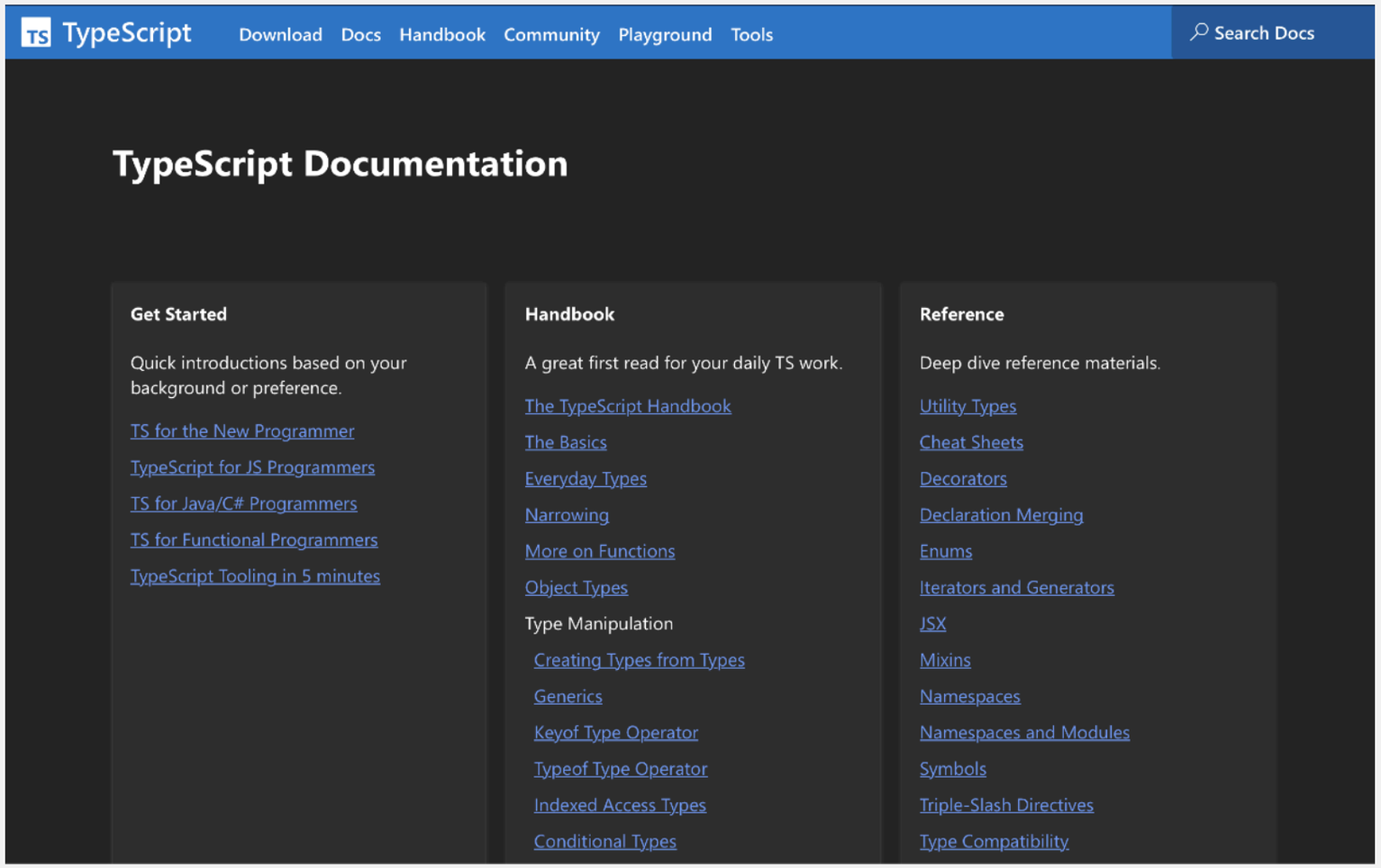
Static Information Gathering: Use an IDE!





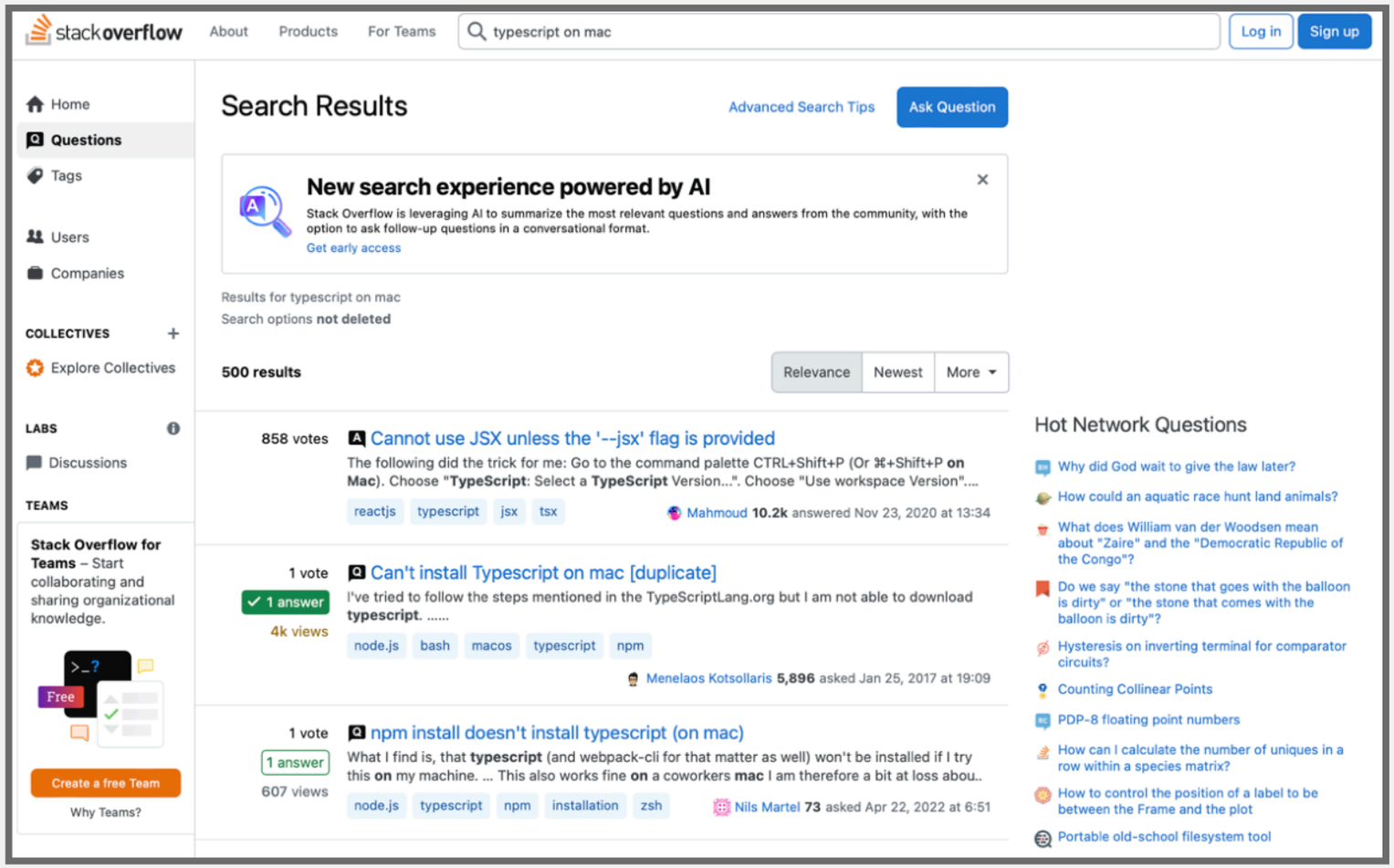
Consider Documentation and Tutorials Judiciously

- Great for discovering entry points!
- Can teach you about general structure, architecture (more on this later in the semester)
- Often out of date.
- As you gain experience, you will recognize more of these, and you will immediately know something about how the program works
- Also: discussion boards; issue trackers



Discussion Boards and Issue Trackers

- Software is written by people.
- How can we talk to them?
- Fortunately, they probably aren't dead.
- So, you can report problems on GitHub.
- Or, ask them questions on StackOverflow.

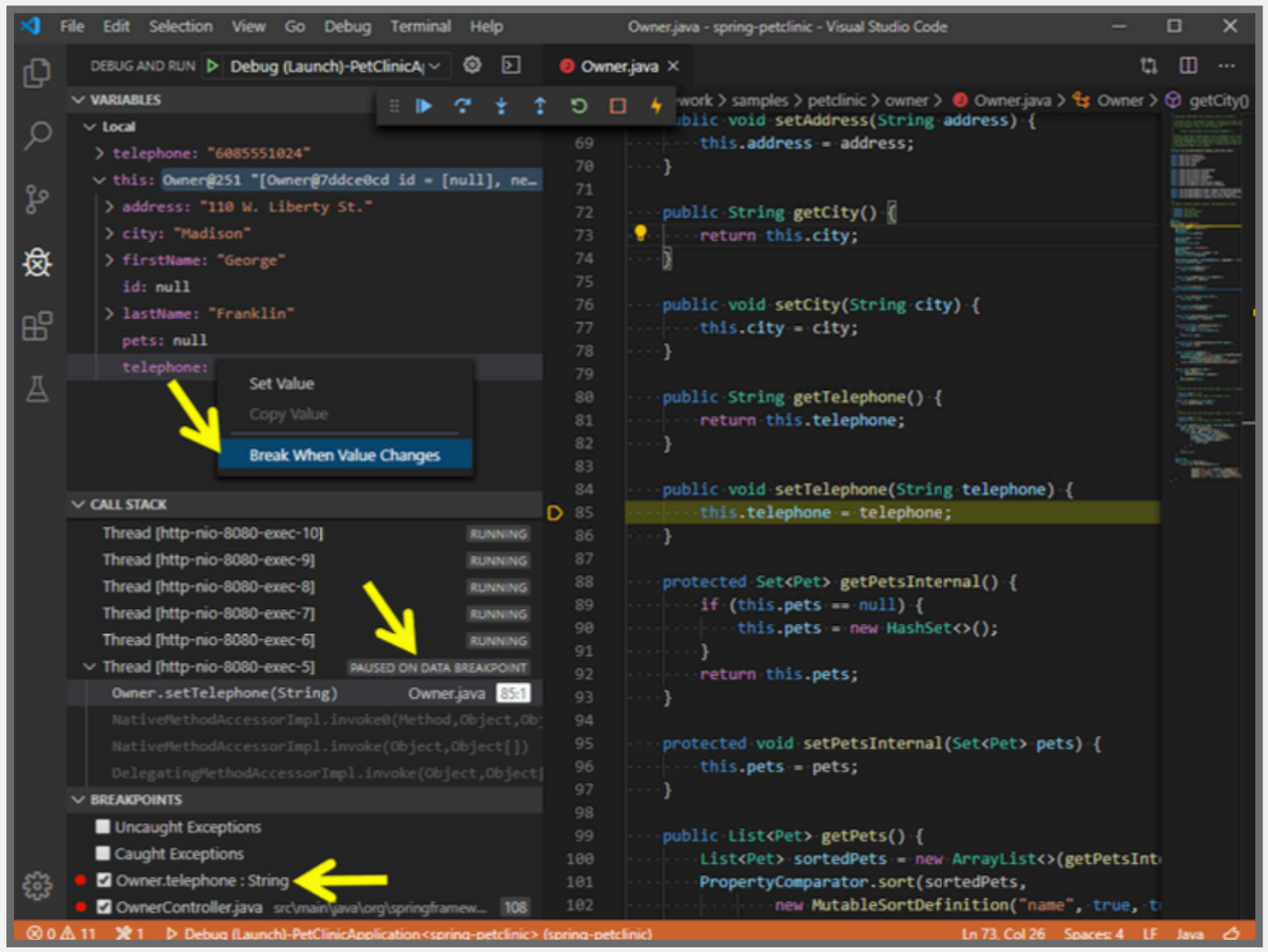


Dynamic Information Gathering

- Build it.
- Run it.
- Change it.
- Run it again.
- How did the behavior change?

Probes: Observe, Control, or "Lightly" Manipulate Execution

- print("this code is running!")
- Structured logging
- Debuggers
  - Breakpoint, eval, step through / step over
  - (Some tools even support remote debugging)
- Delete debugging
- Chrome Developer Tools

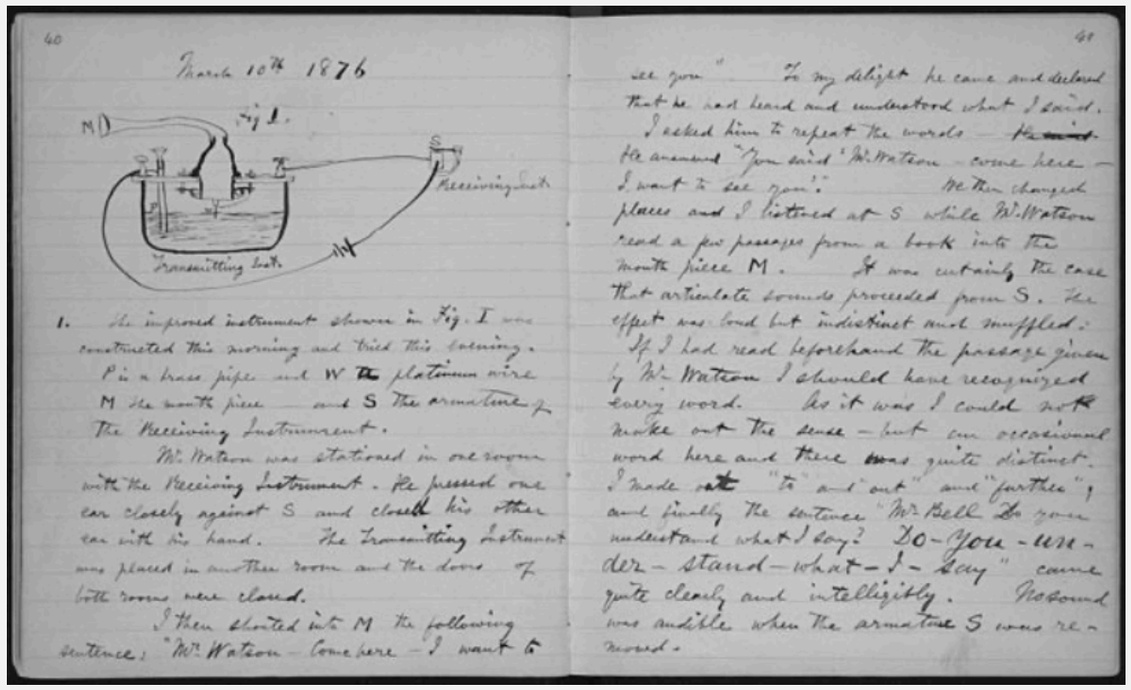


Step 0: Sanity Check Basic Model + Hypotheses

- *Confirm that you can build and run the code.*
  - Ideally both using the tests provided, and by hand.
- *Confirm that the code you are running is the code you built*
- *Confirm that you can make an externally visible change*
- *How? Where? Starting points:*
  - Run an existing test, change it
  - Write a new test
  - Change the code, write or rerun a test that should notice the change
- *Ask someone for help*

Document and Share Your Findings!

- Update README and docs
  - Or better: use a Developer Wiki
  - Use Mermaid for diagrams
- Screencast on Twitch
- Collaborate with others
- Include negative results, too!



Metrics & Measurement

Goals for Today

- Use measurements as a decision tool to reduce uncertainty
- Understand difficulty of measurement; discuss validity of measurements
- Provide examples of metrics for software qualities and process
- Understand limitations and dangers of decisions and incentives based on measurements

Software Engineering

- Software Engineering: Principles, practices (technical and non-technical) for confidently building high-quality software.

What does this mean?
How do we know?
-> Measurement & Metrics are key concerns

Case Study: Autonomous Vehicles

Case Study: Autonomous Vehicles

- By what methods can we judge AV software quality (e.g., safety)?

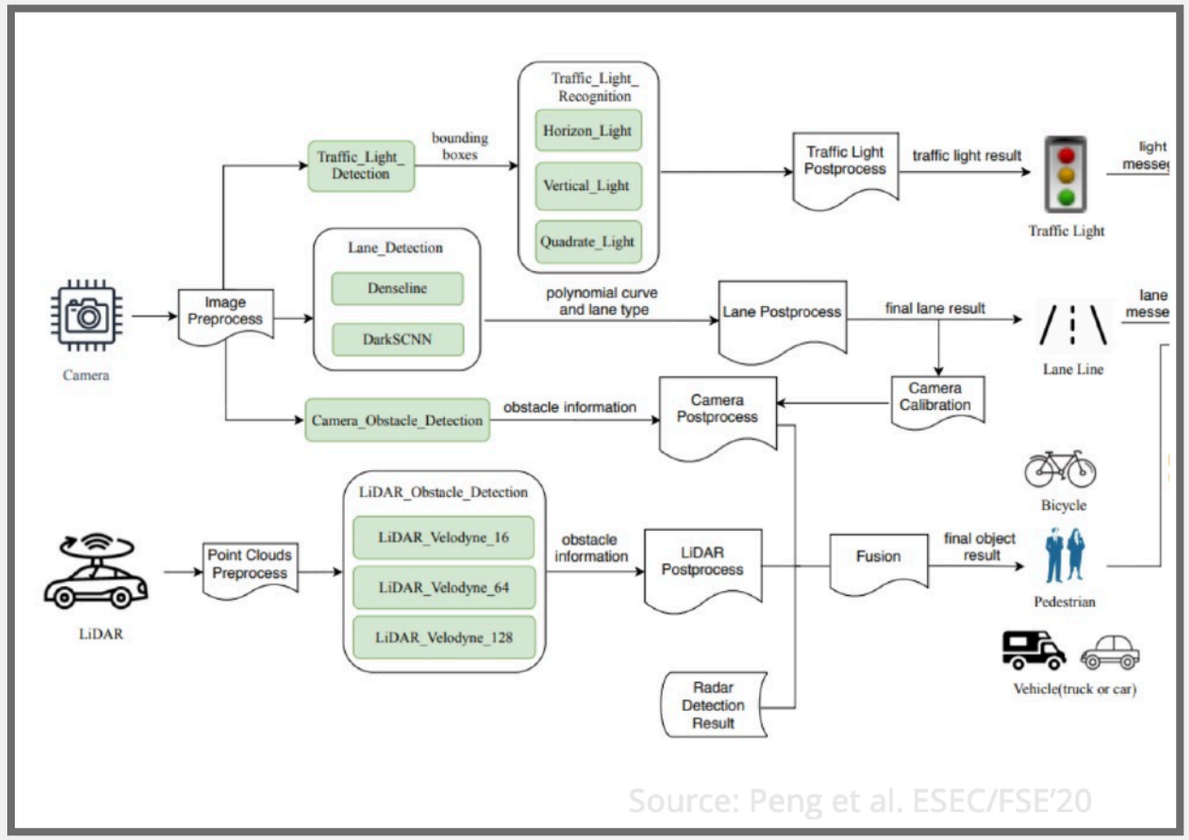
Test Coverage

- Amount of code executed during testing.
- Statement coverage, line coverage, branch coverage, etc.
- E.g., 75% branch coverage -> 3/4 if-else outcomes have been executed

```
        :          :
        :       1698 : const TrajectoryPoint& StGraphData::init_point() const { return init_point_; }
        :          :
        :       2264 : const SpeedLimit& StGraphData::speed_limit() const { return speed_limit_; }
        :          :
        :     212736 : double StGraphData::cruise_speed() const {
[ - + ]:     212736 :   return cruise_speed_ > 0.0 ? cruise_speed_ : FLAGS_default_cruise_speed;
        :          : }
        :          :
        :       1698 : double StGraphData::path_length() const { return path_data_length_; }
        :          :
        :       1698 : double StGraphData::total_time_by_conf() const { return total_time_by_conf_; }
        :          :
        :       1698 : planning_internal::STGraphDebug* StGraphData::mutable_st_graph_debug() {
        :       1698 :   return st_graph_debug_;
        :          : }
        :          :
        :        566 : bool StGraphData::SetSTDrivableBoundary(
        :          :     const std::vector<std::tuple<double, double, double>>& s_boundary,
        :          :     const std::vector<std::tuple<double, double, double>>& v_obs_info) {
[ + - ]:        566 :   if (s_boundary.size() != v_obs_info.size()) {
        :          :     return false;
        :          :   }
[ + + ]:      40752 :   for (size_t i = 0; i < s_boundary.size(); ++i) {
        :      80372 :     auto st_bound_instance = st_drivable_boundary_.add_st_boundary();
        :     160744 :     st_bound_instance->set_t(std::get<0>(s_boundary[i]));
        :     120558 :     st_bound_instance->set_s_lower(std::get<1>(s_boundary[i]));
        :     120558 :     st_bound_instance->set_s_upper(std::get<2>(s_boundary[i]));
[ - + ]:      40186 :     if (std::get<1>(v_obs_info[i]) > -kObsSpeedIgnoreThreshold) {
        :          0 :       st_bound_instance->set_v_obs_lower(std::get<1>(v_obs_info[i]));
        :          :     }
[ + + ]:      40186 :     if (std::get<2>(v_obs_info[i]) < kObsSpeedIgnoreThreshold) {
        :      50254 :       st_bound_instance->set_v_obs_upper(std::get<2>(v_obs_info[i]));
        :          :     }
        :          :   }
```

Model Accuracy

- Train machine-learning models on labelled data (sensor data + ground truth).
- Compute accuracy on a separate labelled test set.
- E.g., 90% accuracy implies that object recognition is right for 90% of the test inputs.



Source: Peng et al. ESEC/FSE'20

Failure Rate

- Frequency of crashes / fatalities
- Per 1,000 rides, per million miles, per month (in the news)

Mileage

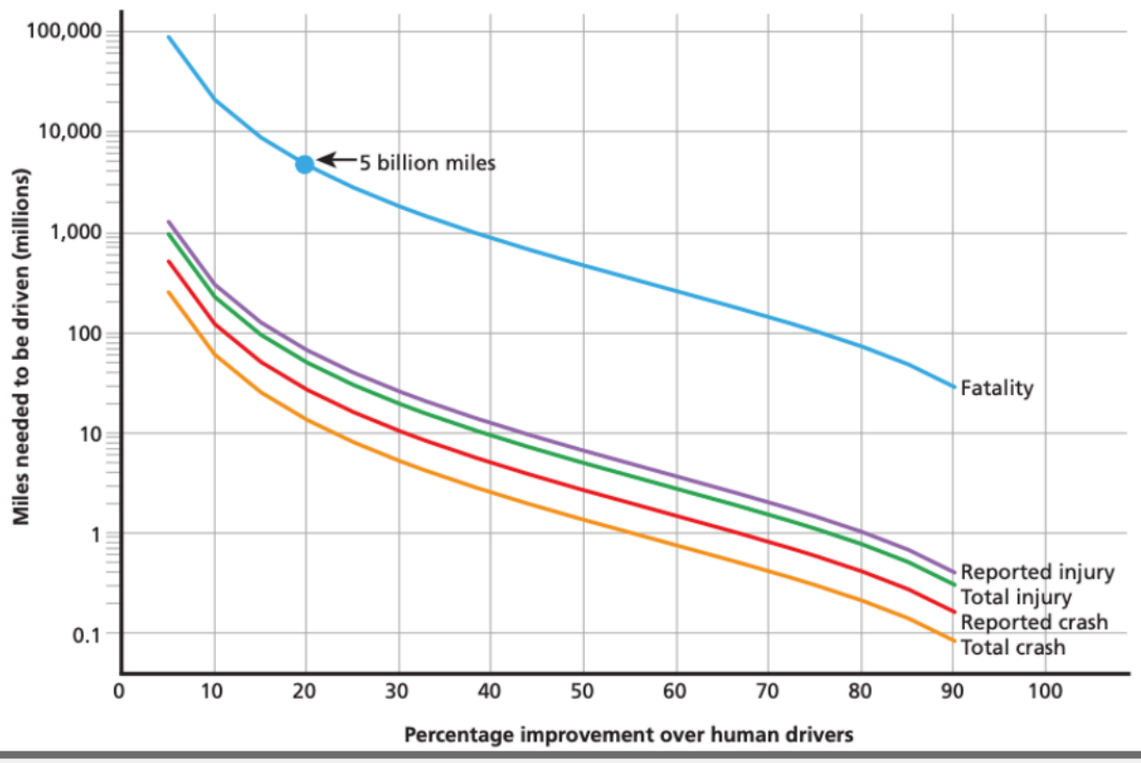
RAND CORPORATION

Driving to Safety

How Many Miles of Driving Would It Take to Demonstrate Autonomous Vehicle Reliability?

Nidhi Kalra, Susan M. Paddock

Figure 3. Miles Needed to Demonstrate with 95% Confidence that the Autonomous Vehicle Failure Rate Is Lower than the Human Driver Failure Rate



Source: waymo.com/safety (September 2021)

What is Measurement?

- Measurement is the empirical, objective assignment of numbers, according to a rule derived from a model or theory, to attributes of objects or events with the intent of describing them. – Craner, Bond, “Software Engineering Metrics: What Do They Measure and How Do We Know?”

- A quantitatively expressed reduction of uncertainty based on one or more observations. – Hubbard, “How to Measure Anything ...”

Software Quality Metrics

- IEEE 1061 definition: “A software quality metric is a function whose inputs are software data and whose output is a single
  numerical value that can be interpreted as the degree to which the software possesses a given attribute that affects its quality.”

- Metrics have been proposed for many quality attributes; may define own metrics

What Software Qualities Do We Care About?

- Functionality (e.g., data integrity)
- Scalability
- Security
- Extensibility
- Bugginess
- Documentation
- Performance
- Installability
- Availability
- Consistency
- Portability
- Regulatory compliance

What Process Qualities Do We Care About?

- On-time release
- Development speed
- Meeting efficiency
- Conformance to processes
- Time spent on rework
- Reliability of predictions
- Fairness in decision making
- Number of builds
- Code review acceptance rate
- Regulatory compliance

- Measure time, costs, actions, resources, and quality of work packages; compare with predictions
- Use information from issue trackers, communication networks, team structures, etc...

What People Qualities Do We Care About?

- Developers
  - Maintainability
  - Performance
  - Employee satisfaction and well-being • Communication and collaboration
  - Efficiency and flow
  - Satisfaction with engineering system • Regulatory compliance

- Customers
  - Satisfaction
  - Ease of use
  - Feature usage
  - Regulatory compliance

Everything is Measurable

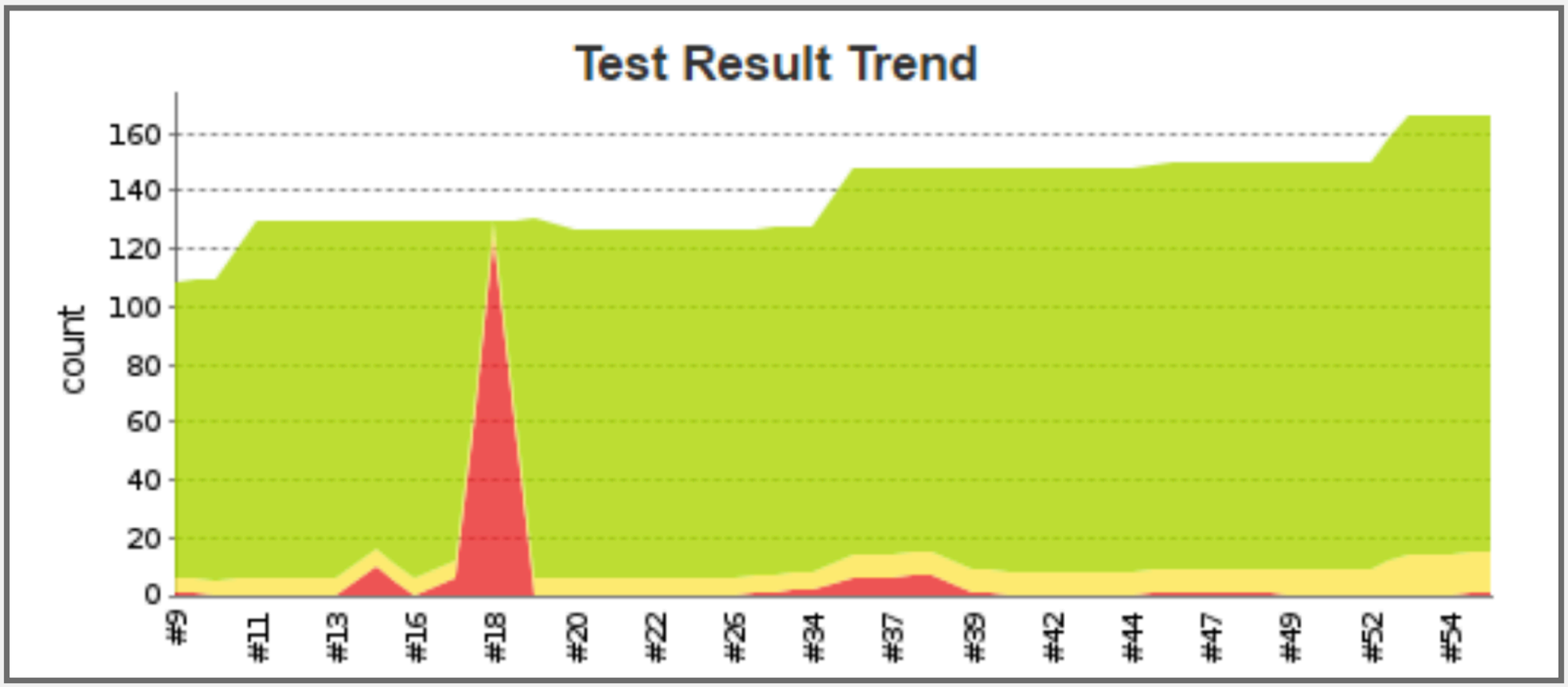
- If X is something we care about, then X, by definition, must be detectable.
  - How could we care about things like “quality,” “risk,” “security,” or “public image” if these things were totally undetectable, directly or indirectly?
  - If we have reason to care about some unknown quantity, it is because we think it corresponds to desirable or undesirable results in some way.
- If X is detectable, then it must be detectable in some amount.
  - If you can observe a thing at all, you can observe more of it or less of it 21
- If we can observe it in some amount, then it must be measurable.

Why Measure?

Measurement for Decision Making

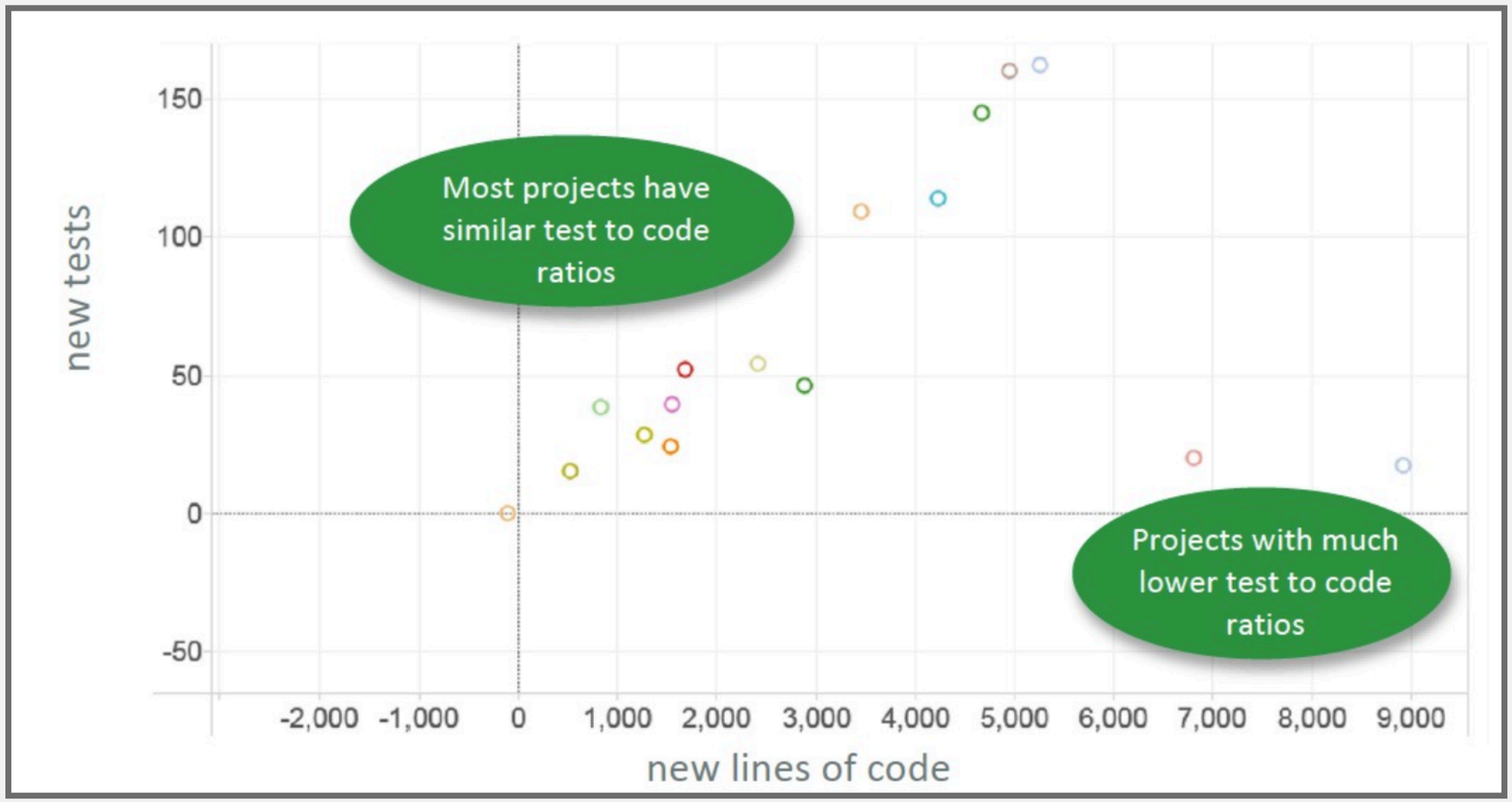
- Fund project?
- More testing?
- Fast enough? Secure enough?
- Code quality sufficient?
- Which feature to focus on?
- Developer bonus?
- Time and cost estimation? Predictions reliable?

Trend Analyses



Benchmarking Against Standards

- Monitor many projects or many modules, get typical values for metrics
- Report deviations

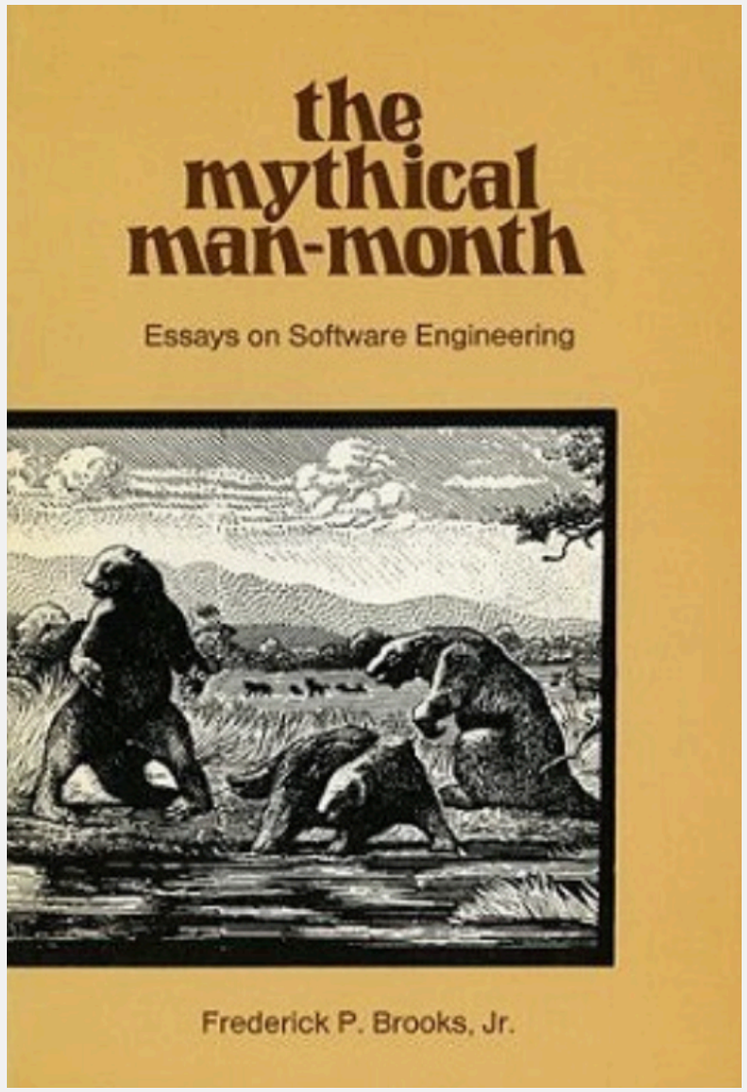


Antipatterns in Effort Estimation

- IBM in the 60s: Would account in “person-months”
  e.g. Team of 2 working 3 months = 6 person-months

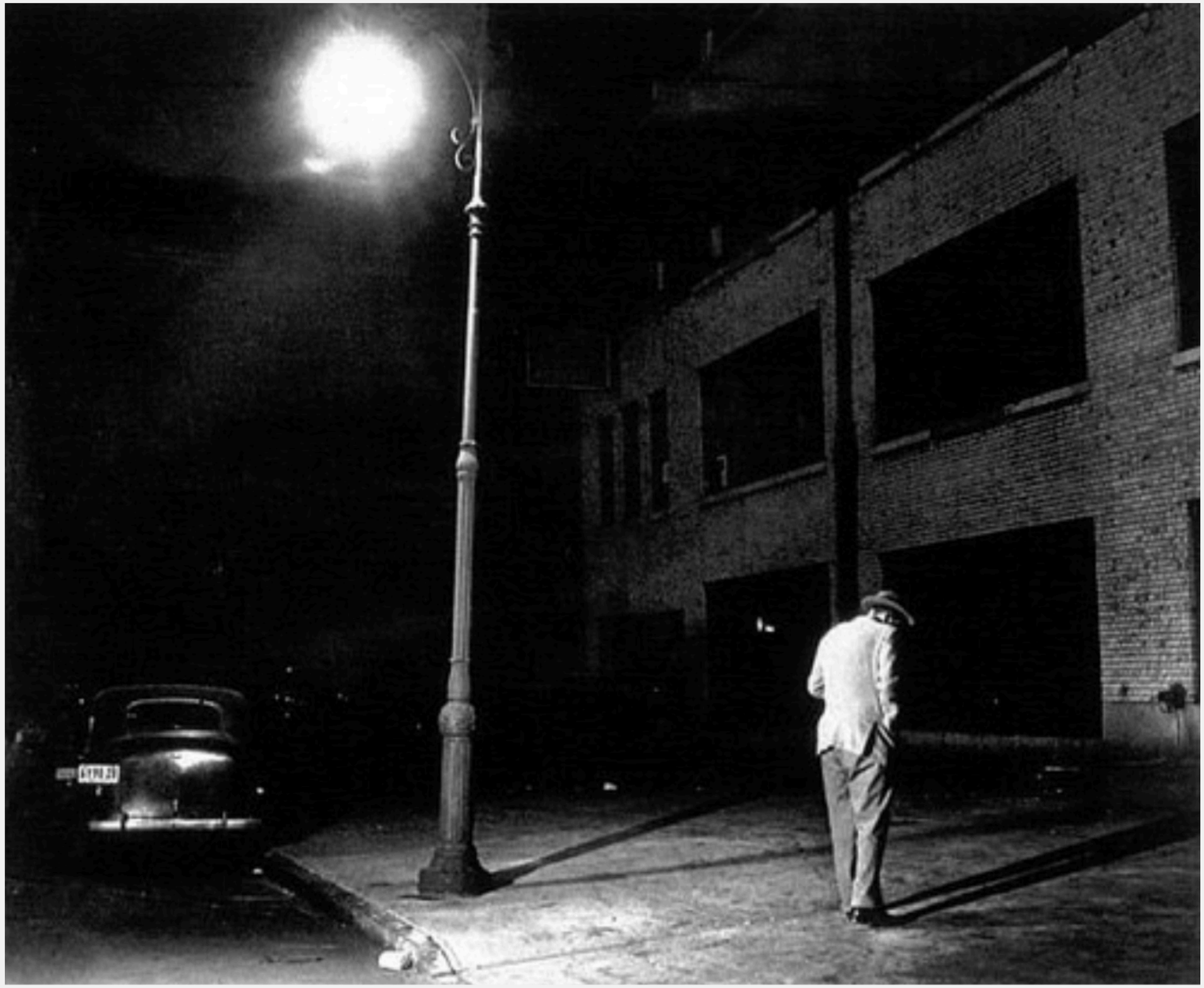
- LoC ~ Person-months ~ $$$

- Brooks: “Adding manpower to a late software project [just] makes it later.”



Measurement is Difficult

The Streetlight Effect

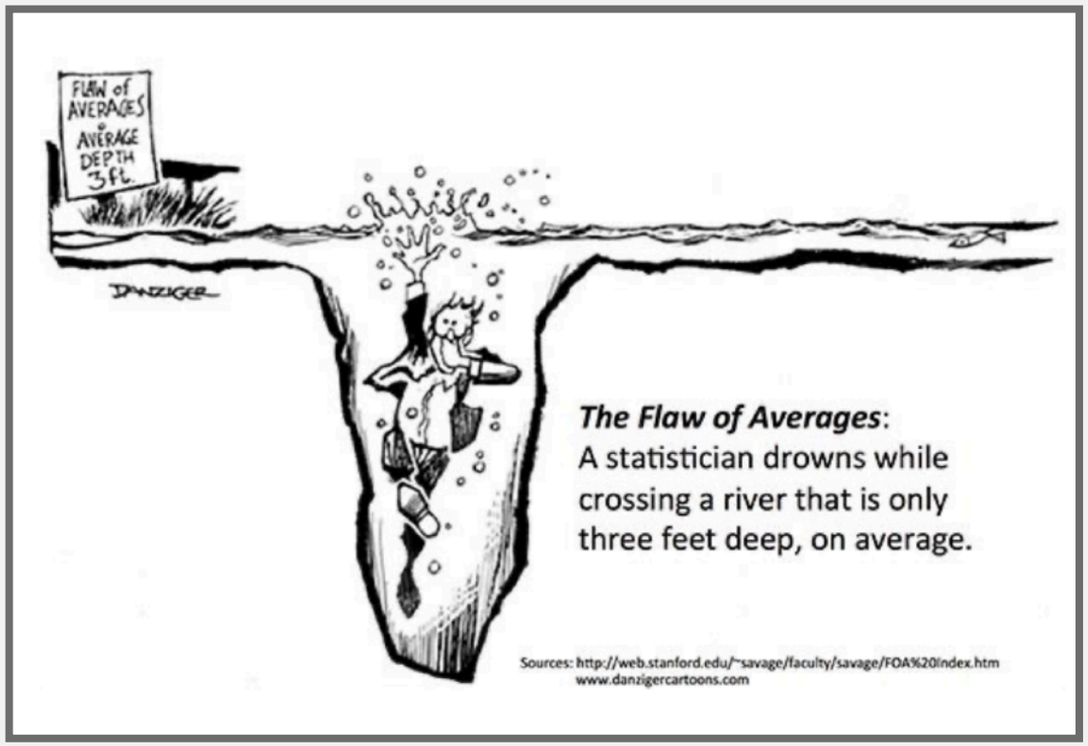


The Streetlight Effect

- A known observational bias.
- People tend to look for something only where it's easiest to do so.
- If you drop your keys at night, you'll tend to look for it under streetlights.

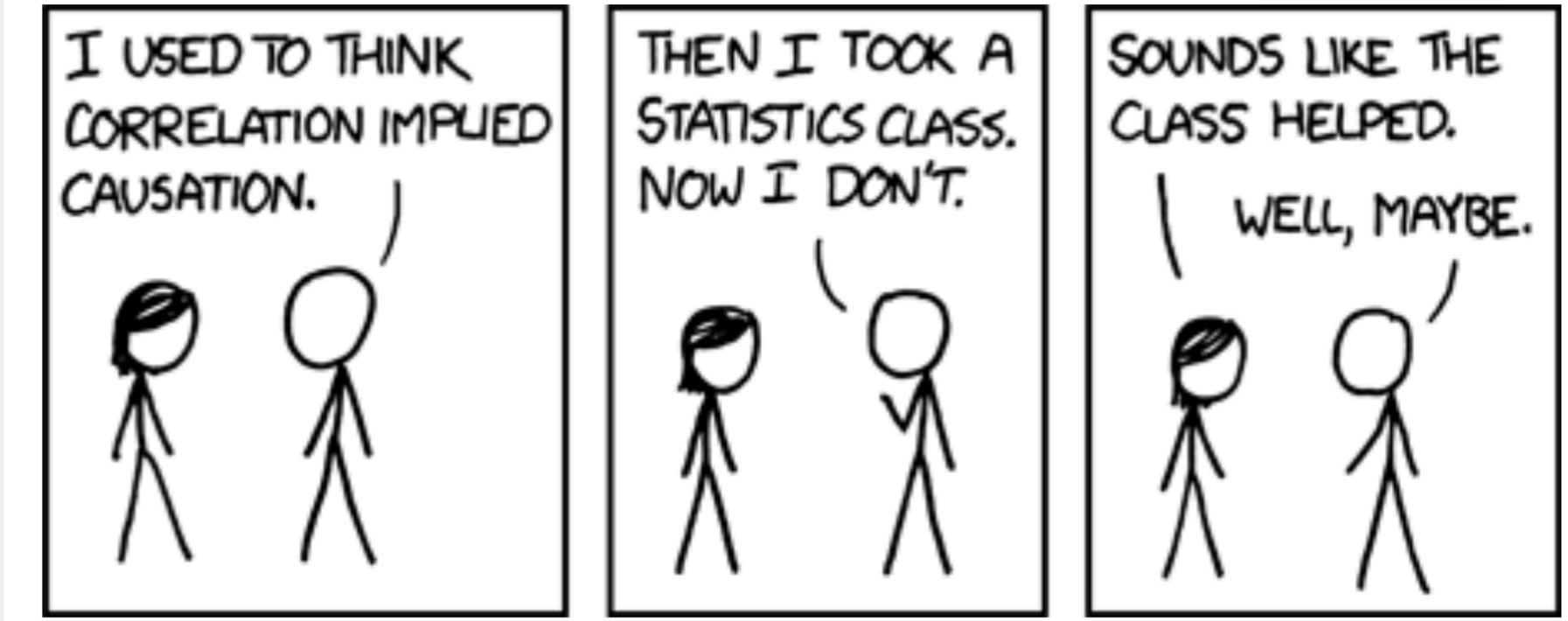
What could Possibly go Wrong?

- Bad statistics: A basic misunderstanding of measurement theory and what is being measured.
- Bad decisions: The incorrect use of measurement data, leading to unintended side effects.
- Bad incentives: Disregard for the human factors, or how the cultural change of taking measurements will affect people.



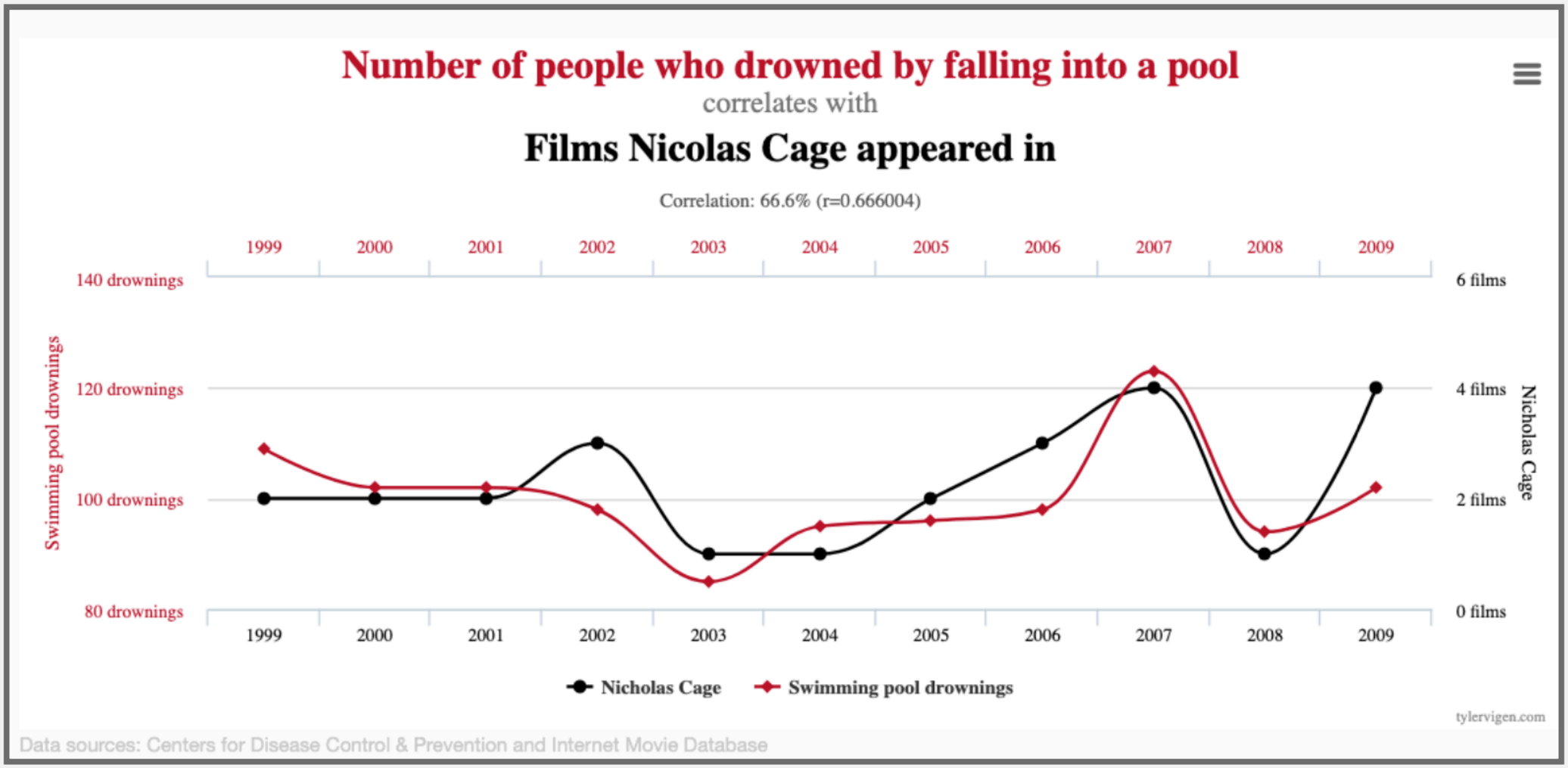
Making Inferences

http://xkcd.com/552/

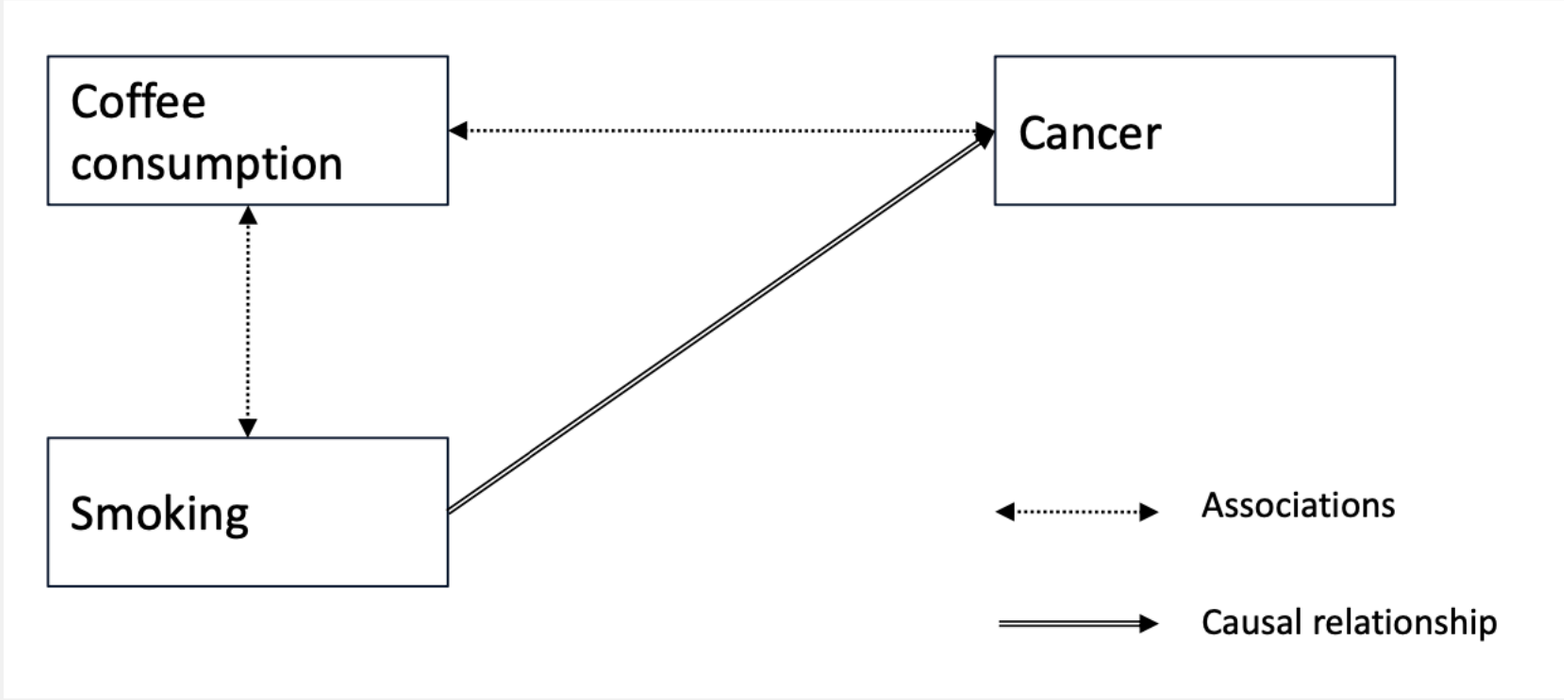


- To infer causation:
  - Provide a theory (from domain knowledge, independent of data)
  - Show correlation
  - Demonstrate ability to predict new cases (replicate/validate)

Spurious Correlations



Confounding Variables



- If you look only at the coffee consumption → cancer relationship, you can get very misleading results
- Smoking is a confounder

SWE Research

RESEARCH-ARTICLE

Coverage is not strongly correlated with test suite effectiveness

Authors: Laura Inozemtseva, Reid Holmes Authors Info & Affiliations

ICSE 2014: Proceedings of the 36th International Conference on Software Engineering • May 2014 • Pages 435–445 • https://doi.org/10.1145/2568225.2568271

"We found that there is a low to moderate correlation between coverage and effectiveness when the number of test cases in the suite is controlled for."

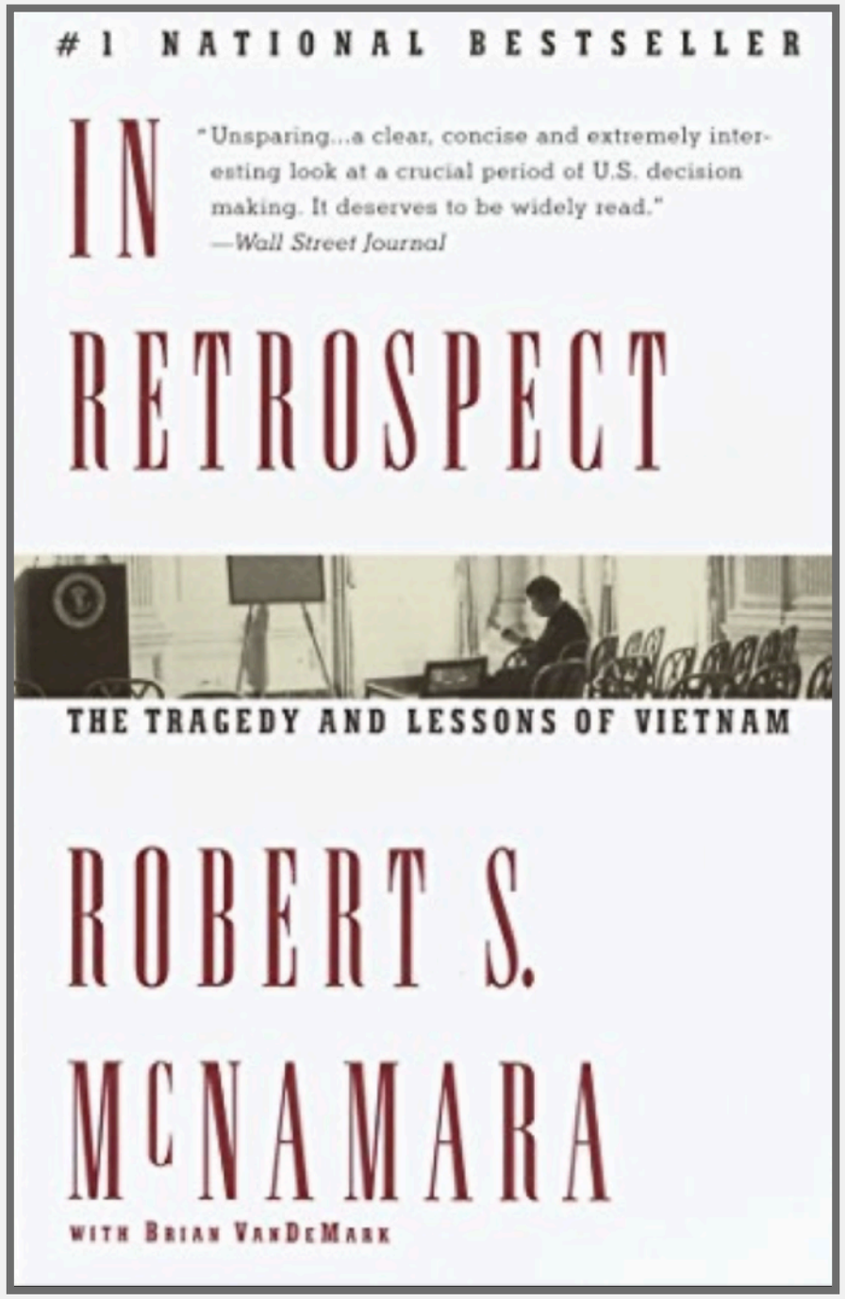
Measurements Validity

- **Construct validity** – Are we measuring what we intended to measure?
- **Internal validity** – The extent to which the measurement can be used to explain some other characteristic of the entity being measured
- **External validity** – Concerns the generalization of the findings to contexts and environments, other than the one studied

Measurements Reliability

- Extent to which a measurement yields similar results when applied multiple times
- Goal is to reduce uncertainty, increase consistency
- Example: Performance
  - Time, memory usage
  - Cache misses, I/O operations, instruction execution count, etc.
- Law of large numbers
  - Taking multiple measurements to reduce error
- Trade-off with cost

McNamara Fallacy



McNamara Fallacy

- Measure whatever can be easily measured.
- Disregard that which cannot be measured easily.
- Presume that which cannot be measured easily is not important.
- Presume that which cannot be measured easily does not exist.

McNamara Fallacy

- There seems to be a general misunderstanding to the effect that a mathematical model cannot be undertaken until every constant and functional relationship is known to high accuracy. This often leads to the omission of admittedly highly significant factors (most of the “intangibles” influences on decisions) because these are unmeasured or unmeasurable. To omit such variables is equivalent to saying that they have zero effect... Probably the only value known to be wrong...

- J. W. Forrester, Industrial Dynamics, The MIT Press, 1961

Metrics & Incentives

- Goodhart's law: "When a measure becomes a target, it ceases to be a good measure."

Simplistic Productivity Measures

- Lines of code per day?
  - Industry average 10-50 lines/day
  - Debugging + rework ca. 50% of time

- • Function/object/application points per month • Bugs fixed?
- Milestones reached?

Incentivizing Productivity

- What happens when developer bonuses are based on
  - Lines of code per day?
  - Amount of documentation written?
  - Low number of reported bugs in their code?
  - Low number of open bugs in their code?
  - High number of fixed bugs?
  - Accuracy of time estimates?

Developer Productivity Myths

- Productivity is all about developer activity
- Productivity is only about individual performance
- One productivity metric can tell us everything
- Productivity measures are useful only for managers
- Productivity is only about engineering systems and developer tools

WARNING!!

- Most software metrics are controversial
  - Usually only plausibility arguments, rarely rigorously validated
  - Cyclomatic complexity was repeatedly refuted, yet is still used
  - “Similar to the attempt of measuring the intelligence of a person in terms of the weight or circumference of the brain”
- Use carefully!
- Code size dominates many metrics
- Avoid claims about human factors (e.g., readability) and quality, unless validated
- Calibrate metrics in project history and other projects
- Metrics can be gamed; you get what you measure

Summary

- Measurement is difficult but important for decision making
- Software metrics are easy to measure but hard to interpret,
  validity often not established
- Many metrics exist, often composed; pick or design suitable metrics if needed
- Careful in use: monitoring vs incentives
- Strategies beyond metrics

Questions to Consider for Your Projects

- What properties do we care about and how do we measure them?
- What is being measured? Does it (to what degree) capture the thing you care about? What are its limitations?
- How should it be incorporated into process?
- What are potentially negative side effects or incentives?