



SPE

Systems – Common Mistakes – PE tools

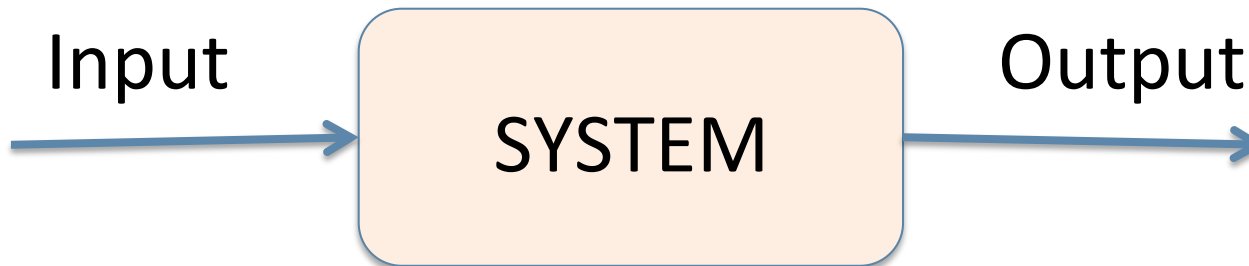
Renato Lo Cigno

<http://disi.unitn.it/locigno/index.php/teaching-duties/spe>

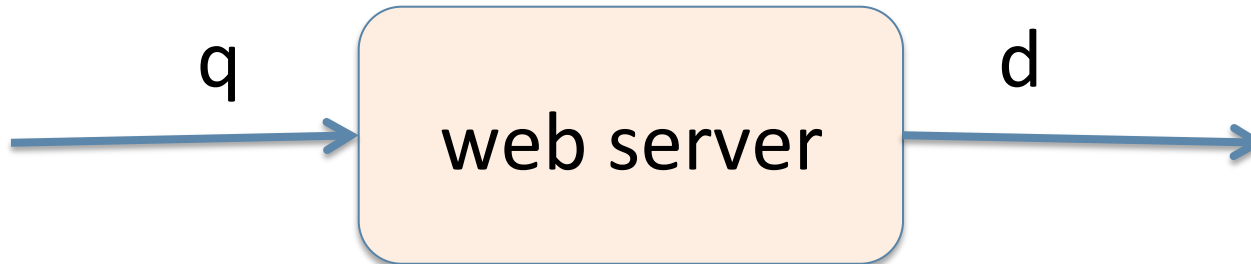


- What is a system?
- Common mistakes in PE
- PE tools
 - Measures
 - Simulations
 - Analysis

- A “system” is any physical or logical ensemble of which we want to measure some metrics
- Normally we wish to predict some “output” given some “input”

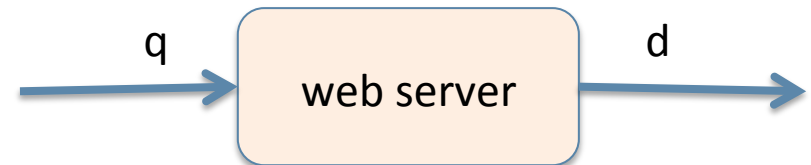


- We are given a “web server”
- Evaluate the service “responsiveness”
- Inputs = queries q_i
- Output = answer delays d_i

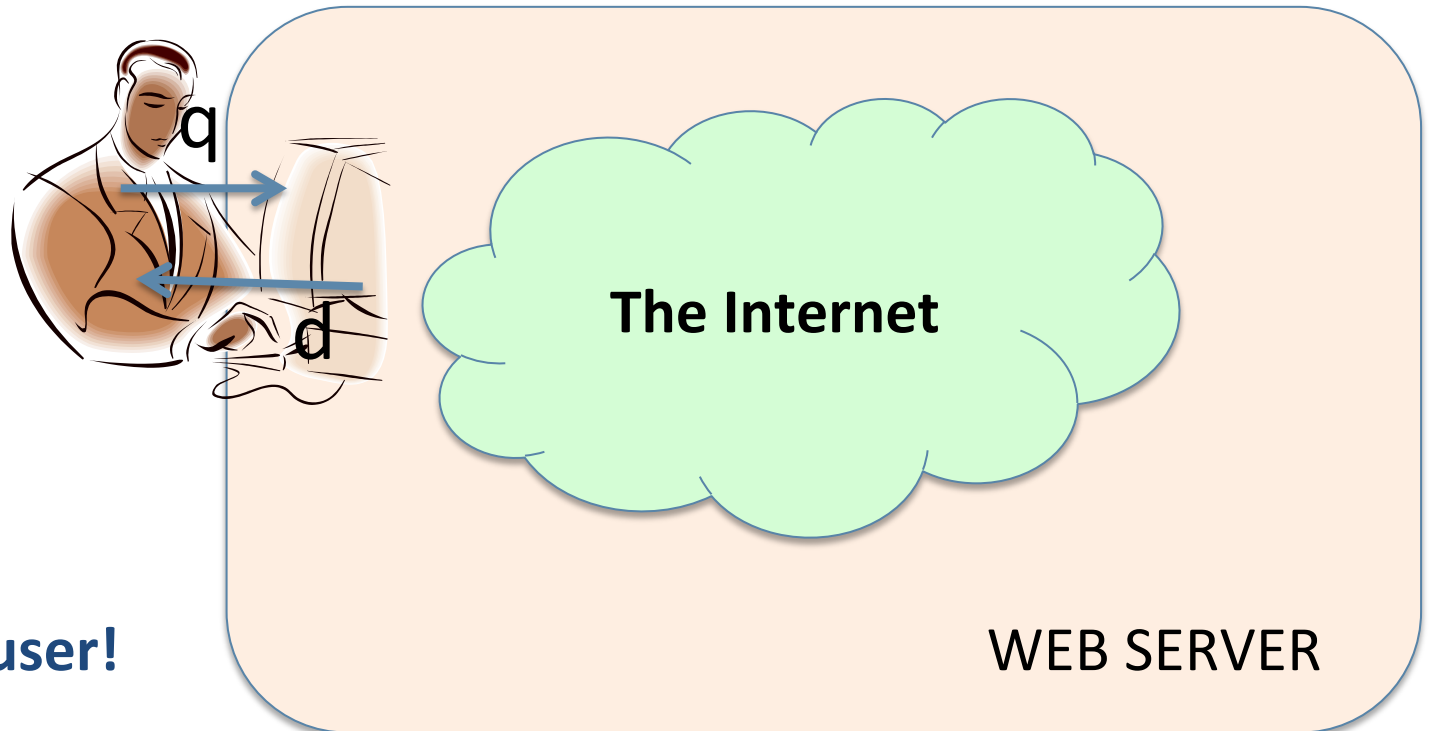




- How do we define a “web server”, what is the goal of our evaluation
 - Hardware?
 - Software?
 - What are the “measurement points” of a web server?
- Is a delay a good measure of responsiveness?
- What are the queries q_i that are meaningful for the evaluation?
- What is the “correct” sequence of queries
 - In PE this is normally called the “workload” of the system under evaluation and its choice is of the utmost importance

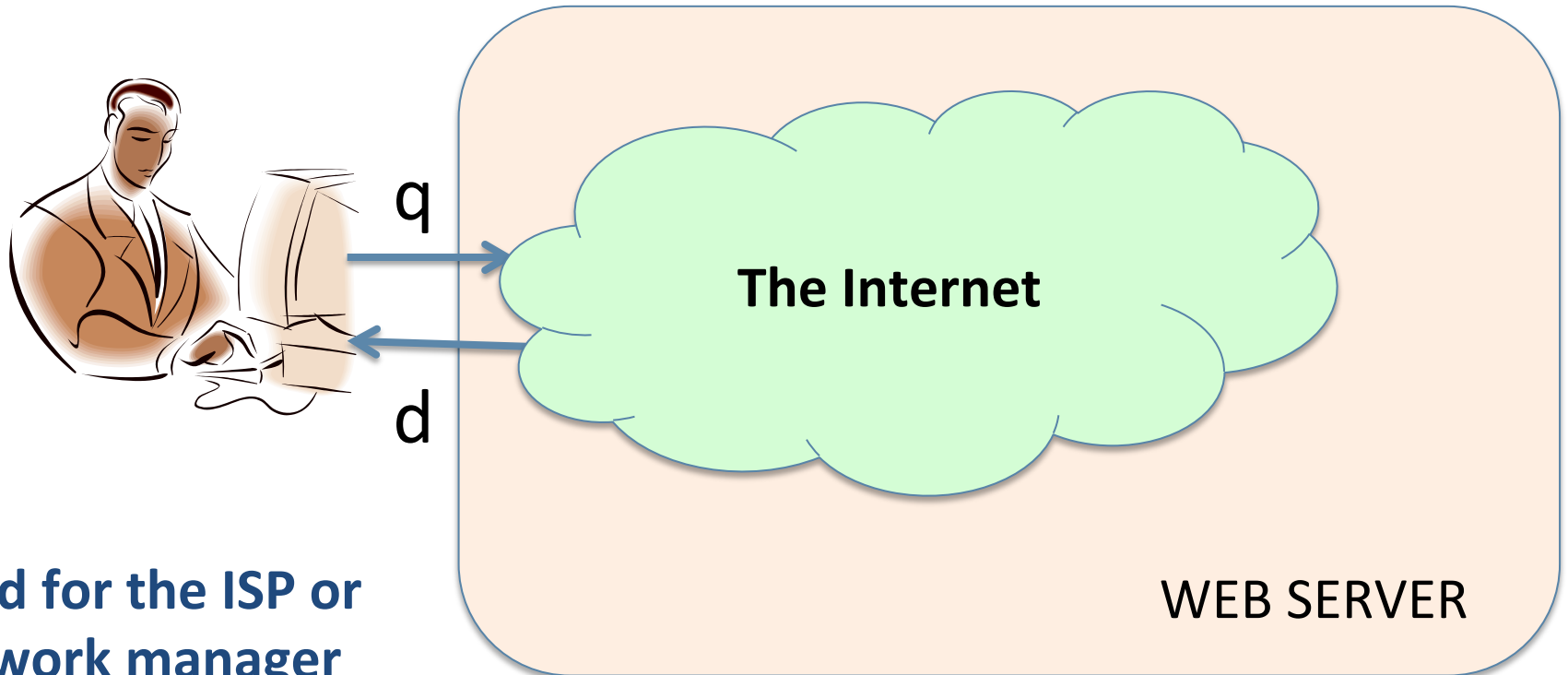


- What is a “web server”?
– (Answer) or Model 1



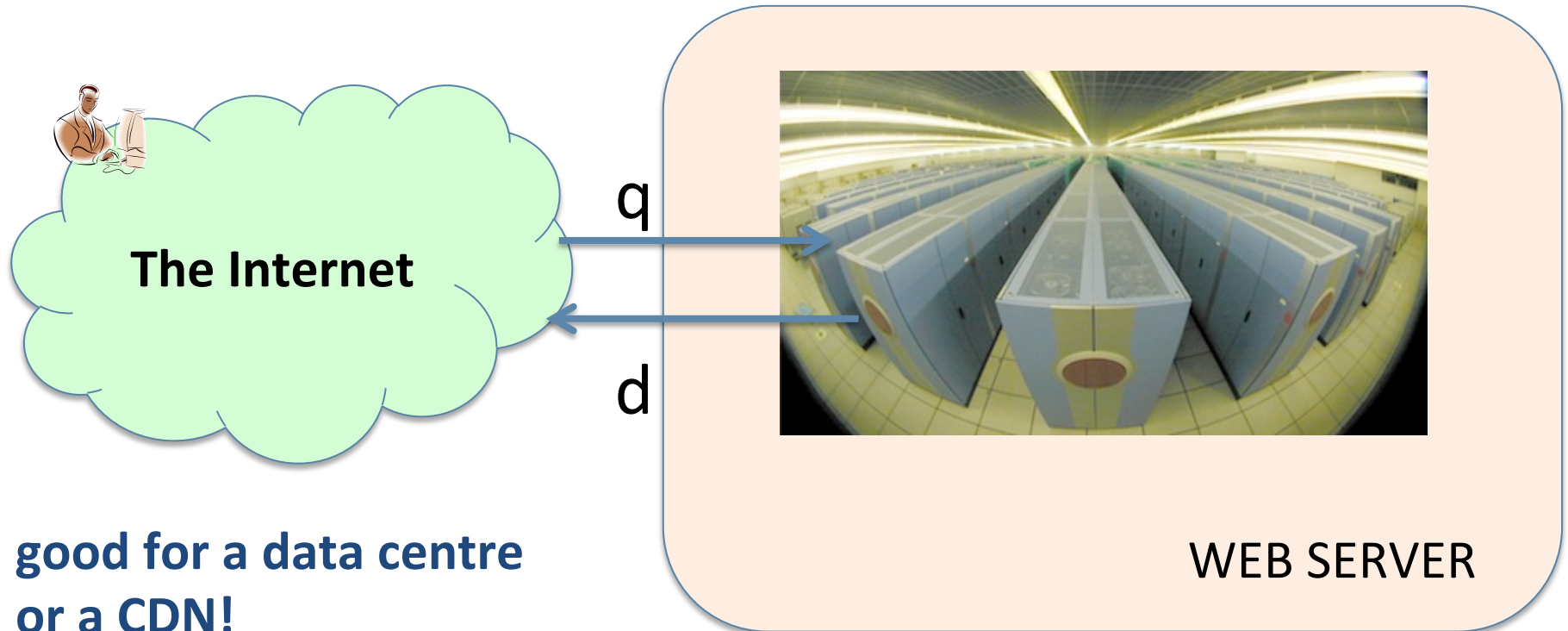
good for the user!

- What is a “web server”?
 - Model 1 bis

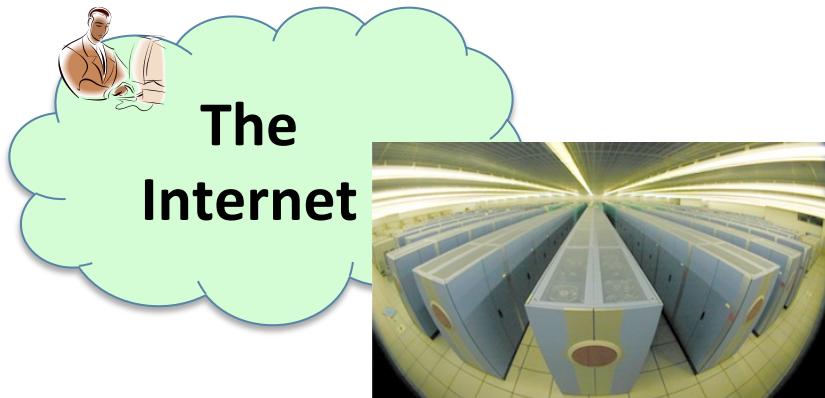


**good for the ISP or
network manager
(your PC is not my business)!**

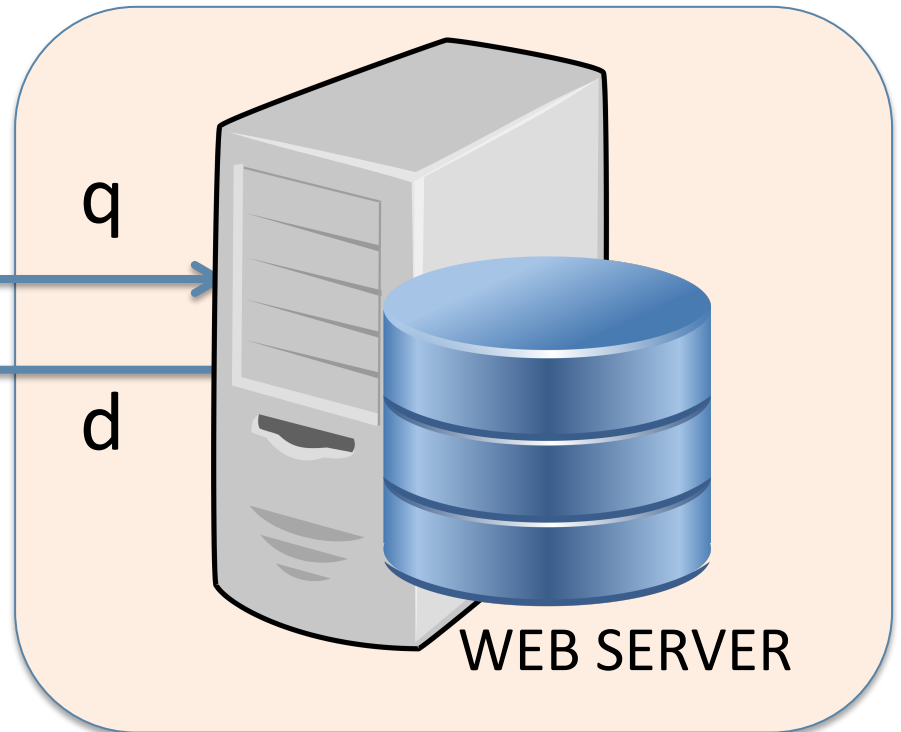
- What is a “web server”?
 - Model 2



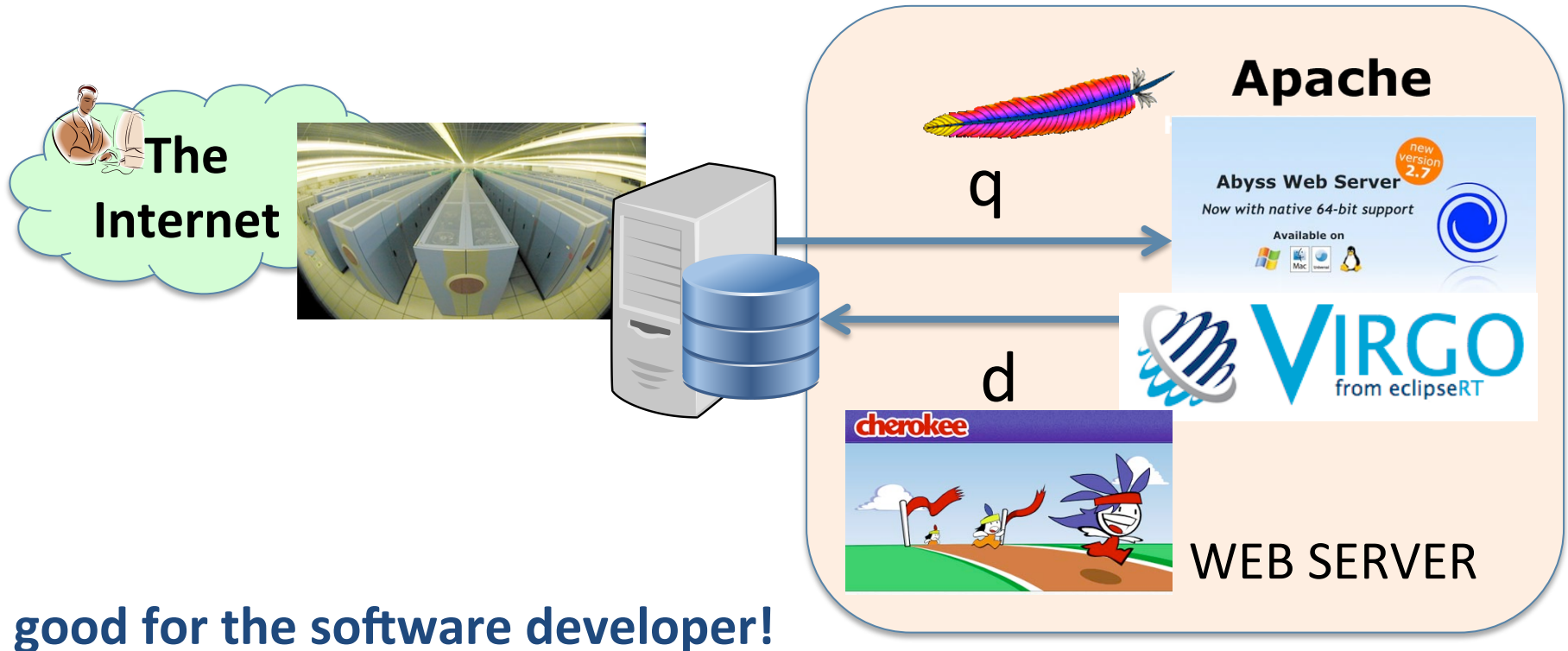
- What is a “web server”?
 - Model 3



**good for the operating system
or an hardware vendor!**

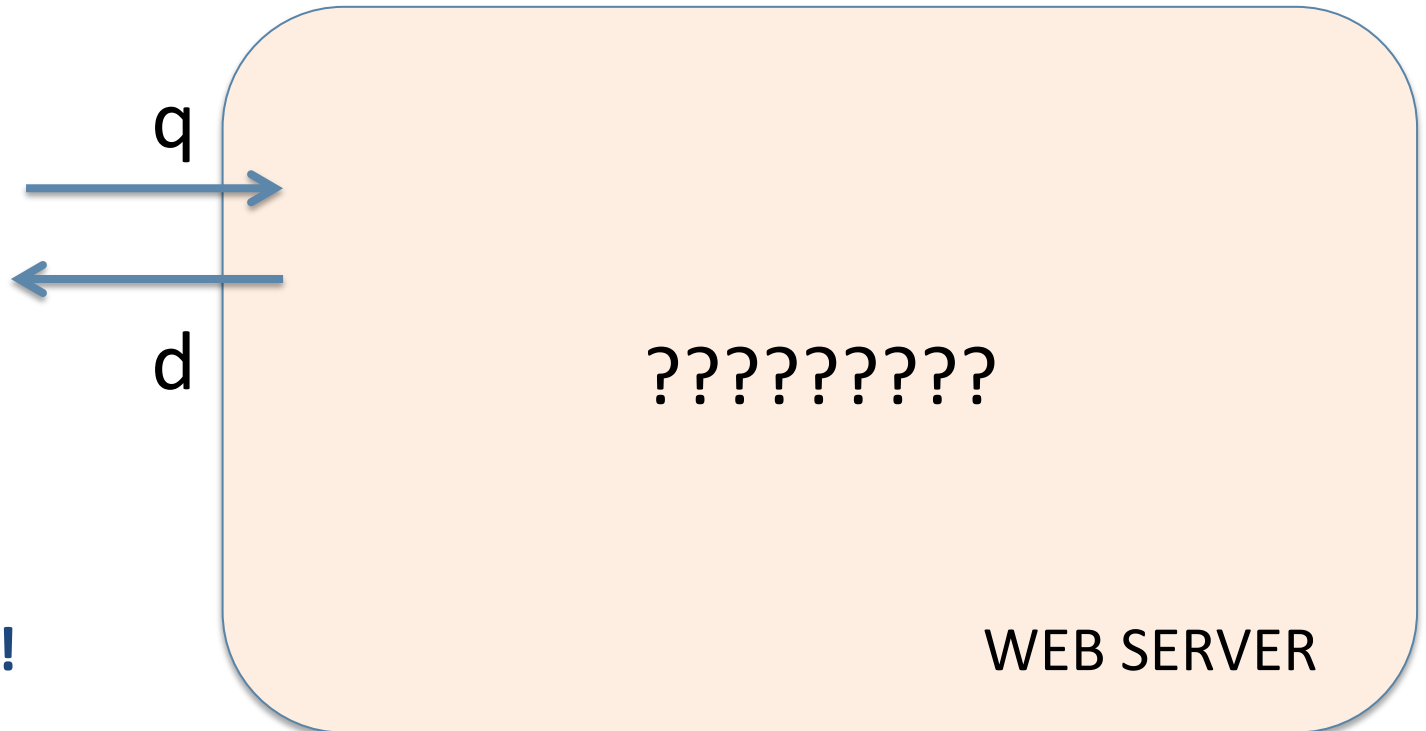


- What is a “web server”?
 - Model 4



good for the software developer!

- What is a “web server”?
 - Model 5



good for you!!



- Different models may require different evaluation tools or techniques
 - Model 1 (specially 1bis) can be easily measured if you seek a “local” answer, but measuring “on average” can simply be impossible
 - Models 2 and 3 can be also easily measured
 - but measures do not give “what-if” answers, so they are not good for design
 - Model 4 is very difficult to measure
- All models can be simulated, but we need to design the simulator correctly
- All models can be prone to analytical solutions, which are fast and easy, but can be very “rough”
 - Very useful to “dimension” systems

- The workload
 - $q_1 \rightarrow d_1 ; q_2 \rightarrow d_2 ; q_3 \rightarrow d_3 ; q_4 \rightarrow d_4 ; \dots$
 - Is it meaningful?
 - Is it representative of all real situations?
- Queries are not isolated and arrive with temporal relationships
 - $Q = \{q_1, t_1; q_2, t_2; q_3, t_3; q_4, t_4; \dots\}$; q_i in \mathbf{q} ; t_i in \mathbf{R}^+ or \mathbf{Z}
 - where \mathbf{q} is the set of all possible queries
 - \mathbf{R}^+ and \mathbf{Z} are real or natural numbers (including zero) depending on time being continuous or discrete



- The workload
- Does the sequence and temporal distribution of the workload influence results?
 - $Q = \{q_1, t_1; q_2, t_2; q_3, t_3; q_4, t_4; \dots\} \rightarrow \{d_1; d_2; d_3; d_4; \dots\}$
 - imply that
 - $Q = \{q_3, t_1; q_2, t_2; q_1, t_3; q_4, t_4; \dots\} \rightarrow \{d_3; d_2; d_1; d_4; \dots\}$
 - **or not??**
- The workload is often called also the “**arrival process**” to the system
- Notice that the PE output is normally NOT the output/service of the system
 - A web server does not yield “delays” it returns web pages!!



- The output: responsiveness
 - What delay are we measuring?
 - Model 1: is the time needed for transmission and for the browser rendering meaningful?
 - Model 4: Database interactions of a CMS is our business?
 - Model 2: If q_i requires back-end computation (e.g., Hadoop), is that to be included or separated?
 - Model 5: Where do you put the probes to measure in-OS performance?



- Projects often fails due to PE analysis failures
 - The system designed does not perform as it should
 - The software project lags way behind schedule
 - Components have not been analysed
 - The development cycle has not been analysed
 - The nuclear reactor explodes when it should not (Chernobil, Fukushima, Three Mile Islands, Superphoenis, ...)
 - The system reliability has not been properly included in PE (TMI)
 - The system dependability has not been included at all (Fukushima)
- PE Analysis often fails due to initial conceptual mistakes



- AKA lack of problem understanding
- Without a model we measure a black-box, not a system
- The measures taken may answer “what”, but never “how” and “why”
- Artificial Intelligence & Machine Learning try to do some analysis on black-boxes
 - They have sophisticated stochastic models behind them
 - The results remains valid until the stochastic model behind is valid
 - e.g., the model assumes that the output distribution has a single mode, if not true the results are not valid



- ***“All Models are Wrong ... some of them are Useful”***
(Mark Twaine, Albert Einstein, George Box or somebody else much more famous than me)
- ***Alternative version 1: “All Models are Right ... most of them are Useless”***
(Unknown, reported by T. Tarpey in a seminar in 2009)
- ***Alternative version 2: “All Predictions are correct ... Unless they regard the Future”***
(maybe Mark Twaine, if not, myself)



- Frequent mistakes in Science & Engineering
 - I want to show that my system is better than his one
 - My boss will fire me if I show that his idea is bogus
- Always present in brochures & commercial datasheets
 - Those are ads, not science
- More often simply lack of pre-analysis
 - I have not given my problem enough time, so my global understanding is not enough to drive the PE process
- Pre-concepts prevent seeing the truth
 - I expect a red ball, and never see the green cube popping out



- I don't know what I need to measure/model
 - Measures taken cannot be interpreted
 - The model I make finally yields no meaningful outputs
 - e.g., results are always constant even changing parameters
- I have a model, but change parameters at random
 - Results taken in this way do not offer insights
- I have so many variables and parameters that the search space is practically infinite
 - Any amount of results will always be negligible w.r.t. to space to be analysed
 - Typical mistake in simulations



- Selection of the correct tool (measures, simulations, analysis) is fundamental
 - e.g., we cannot “measure” a disaster, it’s too late!
 - More later on
- The model must be tailored for the problem
 - Too much details makes it cumbersome & awkward to use
 - Too few details makes results unreliable



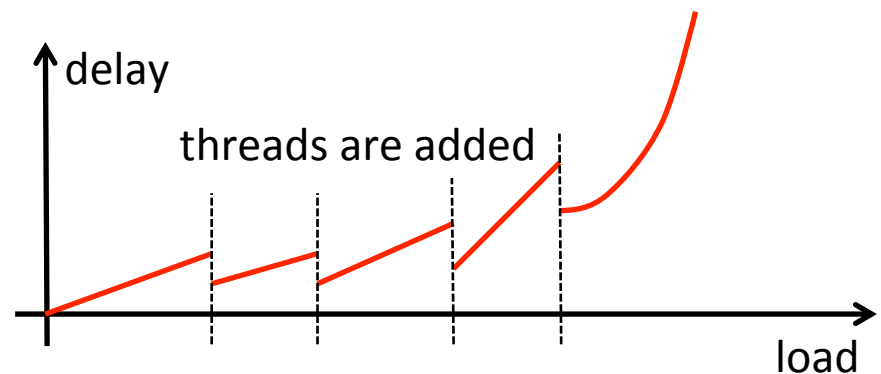
- Outputs depends on the inputs
 - A different input than “thought” leads to wrong interpretations
- Biased workload
 - a skewer random generator
 - a workload that include rare events that never happen during the simulation/measure ... yet they are possible
- Changing one parameter of the workload (e.g., adding new web queries) changes also other parameters that are not controlled (e.g., interaction with data-bases)
 - Also changing variability I also change the mean ...



- Outliers (results that are discarded as not meaningful) must always be checked
 - Instrument fault?
 - “Unlucky” Simulation?
 - Or a mistake in the model/implementation?
- Events that should not happen **must not** be ignored
 - Symptoms of a different system behaviour in measures
 - Symptoms of “eisenbugs” in software (simulations)
 - Symptoms of numerical problems in analytical solutions
 - ...



- This is a “variation” of Impossible & Outliers
- When building the model some important factor is left out
 - Result change when they should not (the “factor” has changed, but we ignore it)
 - We trust our results ... but they are wrong
- E.g., we model a web-server as a single process, while indeed it is multi-threaded with threads added based on a performance threshold





- If two models give the same output the simpler is preferred
- If a model has more than 100 parameters you can obtain any result you want ...
 - This becomes PE as “Parameters Engineering” not as “Performance Evaluation”
- An esoteric explanation is often appealing, but not necessarily the the correct one

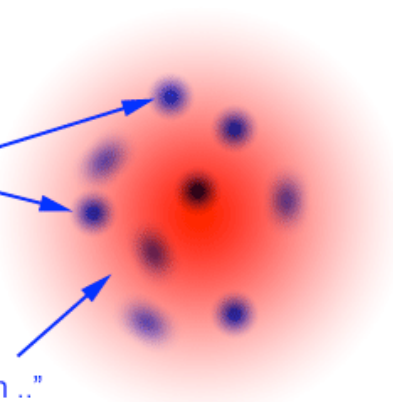
- The model is never put in discussion ... but sometimes it is wrong
- Rutherford vs Thomson Atom is the perfect example
 - The interpretation of scattering was simply impossible with Thomson model

Thomson model

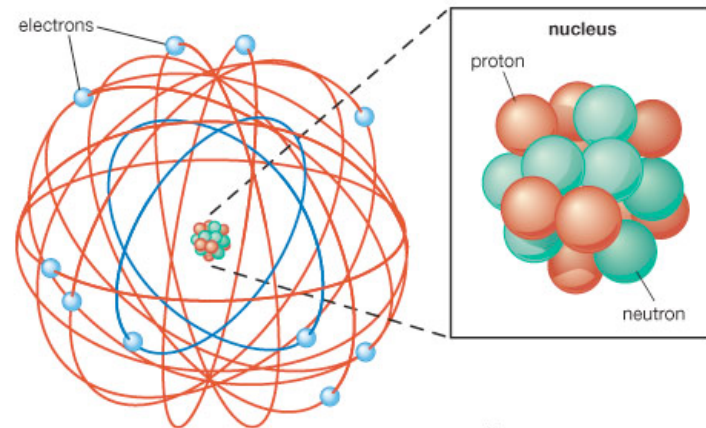
J.J. Thomson's picture of the atom

"corpuscles" (electrons)

"..sphere of uniform positive electrification .."



Rutherford model



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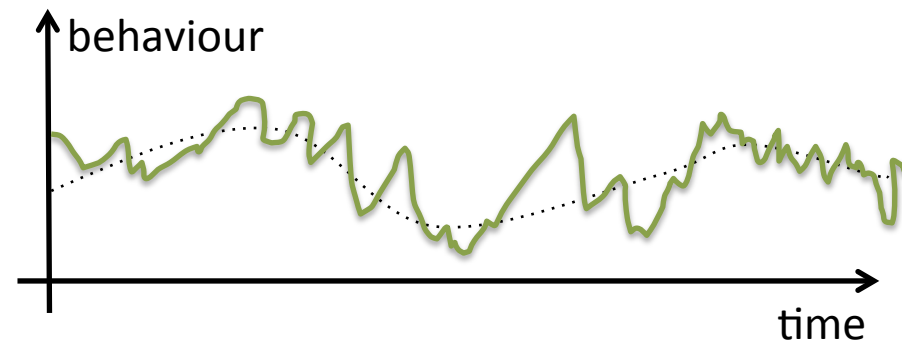
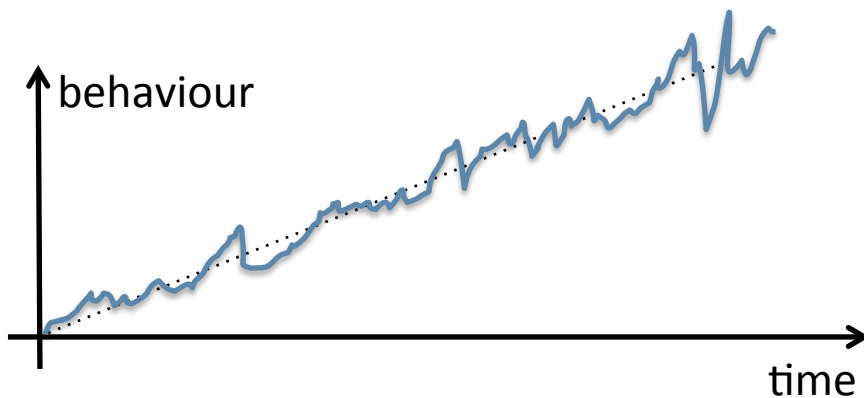


- Stationarity is the property of not changing the behaviour in time:

$$G(t) \approx G(t-t_0) \text{ for all } t_0$$

where \approx indicates a stochastic equivalent behaviour

- Not all systems and phenomena are stationary
 - Interpreting non-stationary systems in light of a stationary model is wrong





- Assumptions and approximations must be very clear (and declared!!)
 - A PE exercise can be OK if I know its goals and validity, but can be rejected entirely if I think it is about the real system
 - E.g., a multi-core CPU approximated as a single core one
- Results presentation is fundamental
 - Graphs are better than tables & numbers
 - Results must be presented with their confidence
 - The results selected for presentation must:
 - Give insight
 - Enable decisions



- The most traditional “scientific experiment”
- The system must be available, accessible and observable
- Workload generation is fundamental and often difficult
 - E.g., loading a 100Gbit/s optical network
- Changing system parameters can be difficult (impossible sometimes)
- Setting probes to take measures might be difficult (impossible sometimes)
 - E.g., adding a hardware counter to a CPU
- Measures must be repeated to achieve confidence



- They are often considered the most reliable PE form
 - But they do not give predictions!
 - You cannot “measure” disasters, you must avoid them!!
- Measures are intrinsically affected by noise
 - Can be additive, multiplicative, or even distortive
 - In any case it is represented by RVs
- Metrics themselves can be stochastic in nature
 - E.g., replication speed of cells; equilibriums in chemicals at high temperature; completion times of jobs in loaded systems; delays in the Internet; ...



- A software that mimics the behaviour of the system
- Requires an abstract model
- State parameters of the system must be carefully selected

$$S(t) = \{s_1, s_2, \dots, s_N\}$$

- Parameter ranges are important and must be checked
- t is inherently discrete: t in \mathbf{Z}
- The evolution of the system is described as conditional random variables

$$S(t+1) = V | S(t)$$

where V is a vector of stationary R.V.



- Workload generation is easier than in measures
- Parametric studies are normally easy
 - But they have a large computational cost
- A simulation “run” is a random walk in the state space of the model
- Simulation runs can be interpreted as Monte-Carlo solutions of the set of couples differential equations that describe the state evolution
- Multiple runs (or batch means techniques) are needed to evaluate the confidence of results



- Finding the model is difficult
- Finding its solutions sometimes even more
- Monte-Carlo numerical integration is normally feasible
 - In this case the analysis becomes hybrid with simulations, but the confidence is normally easier to estimate and sometimes it does not require multiple solutions
- Parametric studies are very simple and effective
- Analytical models are often in the form of dynamic equations
 - i.e., coupled differential equations



$$\left\{ \begin{array}{ll} dG(t)/dt = aF(t) & G(0) = G_0 \\ dF(t)/dt = -bG(t) & F(0) = F_0 \end{array} \right.$$

- A set of coupled differential equations
- This example can describe the evolution of a population G as a function of resources availability F , which in turn decreases as the population G increases
 - Is there an equilibrium?
 - Will G survive or get extinct



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- Measures confirmed with simulations or analysis
 - Insight & Results interpretation
- Analysis confirmed by simulations
 - Be careful not to use the same model!
- Analysis confirmed & tuned with measures
- Simulations confirmed and tuned with measures
- Simulations confirmed by analysis

- Never trust a single tool for PE (if possible)



Tool selection & Tradeoff

| Criterion/Metric | Measure | Simulation | Analysis |
|--------------------|-------------------------|---------------------------|-----------------------------------|
| Stage of design | Prototype – Operational | Any | Any – Very Early |
| Time required | Variable – Long | Variable | Small |
| Design complexity | High | Low – Medium | Variable |
| Accuracy | Variable | Variable | Variable |
| What-If evaluation | Difficult | Computationally expensive | Easy |
| Cost | Very High | Low to Medium | Low |
| Interpretation | Difficult | Medium | Easy |
| Marketing | Easy | Medium | Difficult (lack of understanding) |