Quality Assurance

sh [Professor Maguire]

Magnus Boman will give a presentation about Quality Assurance. For those of you who are in P1, this is particularly important right now - because you will soon start to collect your data, now that you have your draft research plans in. So, pay close attention. For those in P1P2, you have a little more time for it to sink in, but then you need to also apply what it is he is going to say.

[Professor Boman]

Hi everyone! I'm happy to be here and here happy to see you. I have had some email interaction with about forty-two or so of you and those of you. And those of you that belong to my group and will meet tomorrow your room 308 10 to 11:30 to discuss more particulars about your work and where you're at. I know that my data science students some trouble being there tomorrow. I'll set up some sort of person-to-person meeting with you as necessary. Always keep my email - my email address is up there [mab@kth.se] and if you have any questions that you think about tomorrow or next week or in three weeks even if you are not my students, about something that I'm talking about today you're free to email me and I'll try to reply. I just got back from the United States, so a nine-hour time difference, and I've had a lot of coffee, so if I start talking like this, it is because I had too little coffee or too much coffee - take your pick. Can you hear me at the back? Hello, can you hear me at the back? I'm trying to speak up. Yes, so, let see Chip - or is this active now? [Professor Maguire] Yes, it is active now - it is recording. [SOME DISCUSSION ABOUT THE CONTROLS] ... ...

[Professor Boman]

Slide 2: Magnus Boman

So, I'm a professor here at KTH. I have a chair called intelligent software services, which means I am in AI basically. So, I have done artificial intelligence for about twenty years. I also work at SICS, which is a non-profit institute - up here on the sixth floor - conveniently enough - where I work with data science in the so-called DNA lab, and then I've done some more. Blah! Blah! Blah!

Slide 3: Quality AssuranceResources

So, for today I'll talk about quality assurance using some pointers to a book, which I think was good fun to read. It is called "Getting it right", and it is in your [course] material. There are some research papers I'll be mentioning. And some Internet material. So that's what I use for today.

Slide 4: Table 1.1 (From textbook)

And in this book, "Getting it right" in the very beginning, Peter Bock talks about sources of chaos and confusion in a typical R&D group. R&D is research and development. And I'm thinking that this is a pretty good list to start from because it mentions problems with reproducing results (which I will talk about today), speculation mixed with so-called proper conclusions, knowledge versus maybe guess and so on. Your data collection - whereas Chip mentioned the P1 students are there now. Your methods - which I will also talk about. Your processes, the length of your report (being too long or too short) - poorly organized, the documentation of your projects (your code if it involves code), of your mathematical calculations, about your oral presentations which you will do it the end, your visualizations, and your general project activities. So I will basically cover all of these things and more.

Slide 5: N. Eagle, M. Macy, and R. Claxton, 'Network Diversity and Economic Development', *Science*, vol. 328, no. 5981, pp. 1029–1031, May 2010 [Online]. DOI: 10.1126/science.1186605

So, let's start. So, you will recognize the Thames running through London. This is an example from a publication that was published in the journal Science. So there are two journals which most researchers are dying to get published in. I haven't published in either of them - yet - I should say. One is called Science, and one is called Nature. And in this world of impact factors, they have a very high highest impact factor - the highest over 30. Whereas in our area of computer science, I think you'd be hard-pressed to find a journal that has an impact factor higher than 4. This particular example comes from a published work where they were looking at networks of who calls who. So call networks basically. And there are many reasons to study these networks. So one could be if you're interested, like I, in how disease spreads and how you track disease, You can get a clue as to who is meeting with who- who is shaking hands with who, who is transmitting the disease to whom by looking at the very weak signal which is who calls who. As we call our friends, we call our family, we call our employers, we call our colleagues. So, this gives a weak signal about our contact network too. And there are better signals, but this one might be easy to get. Now, the funny thing about the Thames is that- Ah! - Well, what is the funny thing about the Thames when it comes to people calling each other? Anyone want to guess? So, if the river - it is a physical barrier you have to cross it by boat. Yeah? [UNINTELLIGIBLE GUESS] So, while - yes- I think it's a very good guess. The wild guess is that you call people on the other side of the river more than usual people on your side. It is actually the exact opposite, but I like your - I like your guess - because you were - you were thinking. The call network which is not physical in the same sense as the river is. So, we are connecting somehow the logical with the physical. So people don't call other people if they're on the other side of the river to any large extent. And if you do the network analysis properly and zoom in on London, you see that there are, in fact, a special cluster of calls goes to a particular number - which happens to be a support number for a large computer science company. So there are exceptions to this rule. But still, when we - when we collect data, when we look at data, when we analyze data, what we want to do - is we want to find these correlations these link between one kind of network - like the call network and another kind network - which is, for instance, the disease network. And if we're lucky we get published in Science doing so.

Slide 6: Pedro Sanches, KTH, PhD 2015 –Ericsson+SICS/Consider8 project

Here's another example from a project that I was involved with myself - where we look at an ordinary 3D map of the terrain, and then we superimpose on that map things to do with who is where - meeting with whom. So you get these colors, and you get the layers so you can somehow zoom around in people's daily trajectories. So if you are in a meeting, you are sort of in - in like - a like a cylinder together with other people that are in that meeting. And before that cylinder and after that cylinder, you are not together - you are apart. And the telephone call then becomes a smaller cylinder, and so forth.

Slide 7: The Project Hierarchy+TaskCh. 3+4

So in this book, he (Peter Bock) he talks about whenever you do a project - a task together - you need to somehow break it up into subtasks and so forth. So, I'll be jumping between these examples from the real world and from the science world, and then back to the book for a bit.

Slide 8: Reductionism

So what he is building on here is the principle that I've already seen in among my P1P2 groups - that many of you like to employ. It's called reductionism - you just take a hard problem, and you break it down. We do it all the time when we program - we have - we have minor classes and libraries, but we also have subroutines - We do some kind of functional program - we break it down. And the ideas, of course, is that is we solve each simpler part, then we put them together, and we have solved the original problem. So there are a lot of assumptions lying underneath the surface here. One is that by doing that, we actually solve the real problem. So it's not like the original problem had some hidden subproblem that we won't find by taking the pie and separating all of the pieces. So we can, in fact, build the whole pie again by combing these pieces. This was first suggested in the nineteen-thirties by [Rudolf] Carnap. And it has has been talked about by a lot of famous scientists- like Karl Popper and others [Hans] Reichenbach. And the opposite which you sometimes hear people say is holism. In holism, you are you're saying that this sum of all a lot of parts might go somehow beyond just connecting these parts. There might be something that you see only when you look at many aspects at the same time. And a somewhat simplified example is contrasting Western medicine with Eastern medicine - although I don't like these generalizations myself. And if you permit me so in the west I have a problem with my knee, I go to a knee specialist. I go to an orthopedics department of the hospital, and so forth. Whereas in the East, I don't - because there is a connection between how I am living, what I'm eating, and so forth - that doctors there think are connected to the pain in my knee. So, it might be that the cause of my knee pain is actually not located in the knee itself or even the joint or the foot or whatever. It might be something connected to my liver or my neck or my eyesight or whatever. So this means that both sides have their supporters also in science and today people don't use the term holism a lot as it has in science it has a sort of a bad name for whatever reason. So it's often referred to now as the systemic approach. So you can use a systemic approach - you don't break problems down and think that they are done - you look at a whole systemic picture.

Another thing to think about for you when you break down your problems into many parts of and say the other guy in the group is doing these three and I'm doing these three and then we're just putting them together and then we're done is: What if one part proves difficult or maybe even unsolvable. Is the problem then affecting only those parts - you can somehow rework it and solve it? Or does the unsolvability of one part, one piece of the pie being problematic, does it affect the whole pie? That is something you have to solve. So if you were actually eating a pie and sharing it with friends - if someone got a big insect in their - in their piece of the pie - I bet the others would stop eating their pie. So, it might not be that the problem is only with that piece of the pie.

Slide 9: The Project ContextAn Example from Academia

Again to another example from my own research experience. How do you - How do you think about these things - the large picture, the small picture, the whole pie, the pieces of the pie. Well, I was involved for a while with a project that had to do with simulating this whole country Sweden. So as a multiagent system with nine million agents had it has real people in because it was built on registry data. And the reason I did this was that the National Board of Health and Welfare (Socialstyrelsen in Swedish) - they were interested in the cost of vaccine - actually vaccinating the entire population against a particular form of influenza. And they wanted to see the effects of that. And here we have a problem where if you're interested in epidemiology you can't just unleash dangerous pathogens and count how many people are affected. So there is no way of actually carrying out these experiments on a real population, but you can use real data, you can use register data, and you can unleash whatever terrible pathogen you like and count the dead. Because it is just a game, right? But the thing is you once again to connect his game this simulation to the real world and explain that it's actually like this or like that, and then your problem is people say, "Oh! But how do we know your right". You need to validate this. And then again I'm in trouble - yes - if I look at a terrible combination of H. and M. that that would kill a large part of the Swedish population I can't - I can't wait or hope for that to happen just to see if my model is correct. And most likely, there will never be a scenario like the ones that we modeled. So this is a problem where the researcher, the scientist, lives in his or her isolated world - trying desperately to make this connection. This is something that you do too - most of you in your project- you do something in a model, and the model can never be the whole world. Then it is not a model at all; it has to be a simplification.

Slide 10: The Project ContextAn Example from Academia

And you're always part of the bigger picture. It is a bit optimistic to think that I can point. I'm down here - I'm a computational epidemiologist, in this example. So what I'm doing.

[THANKS FOR POIONTER] So I'm down here. And I'm doing the implementation, putting it into a simulator. Then I'm running experiments and maybe doing sensitivity analyses. And then I am waiting for these people, the policymakers to just admire my results and of course, they help me - they help me with the input they said, we know this and that about the population - this should go into your model. And what they do, is they read this output report, and then they look at the real outcome that they somehow compare this as a weak form of validation. This illustration is also an illustration of who is involved in this project. Who are the stakeholders? So, in this case, the stakeholders are the policymakers, they might be politicians, they might also be people in charge of the hospital, people working at the National Board of Health and Welfare at the European CDC, or things like that. They are the problem owners, and they are stakeholders. So something to remember which I will come back to is: Who are the stakeholders for your work? Is it other students, is it politicians, is it ... Who is it? Because when you present your work, you shouldn't just the address your examiners here - you should think about in the best of all worlds - How am I changing this world into an even better world through our work? In order to do that, I need to address the stakeholder[s], and this is always a bit tricky.

Slide 11: Stakeholders

So who could they be? Well, they can be a problem owner; they could be another researcher; they just be citizens, so let's say all the taxpayers, for instance. These days we often hear that they could be an AI; they could be an algorithm waiting for these results; it could be a whole nation-state, like Sweden; policymakers (as in my case), nongovernmental organizations; or a company, and more.

Slide 12: L Brouwers, B Cakici, M Camitz, A Tegnell, and M Boman, 'Economic consequences to society of pandemic H1N1 influenza 2009 – preliminary results for Sweden', *Eurosurveillance*, vol. 14, no. 37, Sep. 2009 [Online]. DOI: [10.2807/ese.14.37.19333-en](10.2807/ese.14.37.19333-en)

So, this particular project had some output - so we said well these are the costs associated - so this was a quantitative analysis which was resting on our simulations - so we could stay the cost of vaccinating the entire Swedish population- most of them twice - would be this big in this scenario. And we had multiple scenarios. So these were all quantitative. But there was also a qualitative side to work that made me end up on the front page of a lot of Norwegian daily newspapers. "Swedish professor -- something about the end of the world" And we were also featured in a National Geographic documentary about the kind of work that scientists do when they try to look at really terrible possible outcomes or threats to humanity. And here in Sweden was a television show called "ten ways to end the world" (I think) and they separate it into threats from nature and threats from ourselves. So threats from ourselves are blowing up the planet using nuclear weapons and things like that. But threats from nature and pandemics were number one. So we sort of won. And then there is the qualitative side to this, so what do you do if you say that, "well, if this happens to three people who come from Southeast Asia to Arlanda Airport and they are infected with H60N9, and it travels like this, and this many people are affected, and then it reaches Stockholm and then Gothenberg" - you paint this scenario. What do people do with this information? Well, they interpret it, and many of them interpret it in qualitative ways, and then they run off and make decisions based on this. And then it's up to you, and here we are almost entering into ethics. So it's up to you: Where is the limit of my responsibility when it comes to what people do with my research? So, where do I say I don't care anymore, or I cannot hear anymore. They made a silly interpretation. Or is there something you can do about how you present your research so that people don't run off and jump to any conclusion that puts you on the first page of Norwegian newspapers.

Slide 13: An Epistemological JourneyCh. 5

Okay. In this book by Peter Bock, he talks about what he calls an epistemological journey. Epistemological means it's about knowledge - from the Greek word "epistēmē" so it's about knowledge. And science, many people say, is a pursuit knowledge. So what do we do this - Well, we need to talk about four things. So, I'll talk about these four things we need to consider: What is research? What is just development? And we need to talk about this reproducibility. About completeness. And about objectivity.

Slide 14: Research vs. Development

So, first research versus development. Well, I put up eight sorts of scales here where you can you can worry about if you like the left side and right side or or well you can you can just look at these as sort of trade-offs or like the beginning of a taxonomy or something. So, in your training here, for instance, this course is about scientific writing: So are you trained to be scientists, or are you trained to be engineers? And does it matter? And if it matters, how does it matter? So hands up, how many people feel that they're being trained to the scientists? I saw some coming up, but then he saw how few hands there were, and you took them down again. Okay. How many that you are being trained to be engineers? Okay. How many feel that you're trying to be food for artificially intelligent robots? So 2, 82, zero. .. So, if you are engineers then and this is scientific writing, then why is this course not called writing for engineers something like that? Well, because they overlap. Right! So, some of the things you do even if you are mainly trained as engineers are to do with science, which means that some of you produce publishable results - publishable in scientific journals, not just journals directed toward engineers. Now, you can think about also: How good is science? And how good is engineering? Because if you - if you look at media, science is always portrayed as something beautiful and something that is good. Science is good for society. It has sort of builtin societal benefits. Whereas engineering, you hear about engineering, for instance, when a bridge collapses, they will say, “it is bad engineering”. So it is not always as good. But you also have a lot of positive examples, like the new opera house in Sydney. It is not just a piece of fantastic architecture; it is also very cleverly engineered. And you hear of Slussen in Stockholm, beautiful then - terrible now. What happened? How do we solve the engineering problem of the water, the traffic, and everything? But this is not the only trade-off when you - when you think about what it is that you do. And what I run I say what you do - I'm not only talking about project work - but your education here in general.

You can think about what does it mean if you - if you produce some code and that code is proprietary versus sort of free to use? So there are no IPR claims on it. What does it mean to be non-profit as opposed to for-profit? What does it mean for software and results to be free & open; and if you check your code in, for instance, on GitHub or if you get promoted on some forum that you read and that you follow? Is it a very small clique of people that will know about your results? If you have a user community, will they all look like you? Is there a nerd factor involved? Or is this something you do, for example, for all taxpayers? And I understand that you know, all of you or most of you, have looked the ethical material - so I already gave you one example of what is the range of your responsibility for your own work. And then something that we all have to worry about now is: How sustainable is your work? And how are you changing the sustainability of whatever problem you are looking at by contributing through your work? This is something that scientists and especially people working in commercial R&D didn't have to think about. But today, all the large companies have serious policies of corporate social responsibility. And sustainability is at the core of this. Many large companies talk about the United Nations' new seventeen goals. Sort of "save the planet" and it's all about sustainability. So, it's there.

Slide 15: Reproducibility

Second - Reproducibility. What is that? Well, it is making it possible for somebody or even you yourself three years from now, for instance, to replicate your own results. And this is considered to be one of the pillars of the scientific method. So let's say there is some called "The Scientific Method", then you cannot produce scientific results unless your results are reproducible. And you often hear people this referred to this under different names. So sometimes called the alignment or docking. You dock your model into another model, or you align your model with somebody else's model. Now, if you do this - if you worry about this- you should make it possible for other people through a ReadMe file, through documentation, or through talking about how people should go about replicating your results. And if you are lucky they can do it, and then your research gets: well, does it get validated or does it verified? Well, traditionally, we separate these two because validation is weaker. Validation means that someone is giving you support by, for instance, reproducing your results. It's a strong way of saying, "Oh! It wasn't depending on your particular machine or your benchmarking or the air in Stockholm. This was a general result, so this has some scientific merit." That is a validation. Verification, we usually say that ultimately proved that something is correct. And that is we know that that is possible in mathematics and some parts of engineering, but it is not always possible - especially if you do more empirical work - so more towards the qualitative side. And an extreme example would be all the code running at the nuclear power plant should be verified - which means that you can never have a routine that jumps out and does something that is something or causes something strange that threatens the security of the installations, for instance. And it's very costly to verify code and to verify scientific results. So it is rarely done. Yes? [UNINTELLIGIBLE QUESTION] ... ... So, you started with the three words "How do you" and then came "feel". How do I feel about it? I feel that, hmmm, I think that I feel there is an honesty among scientists that makes most people don't cheat - so when they say that this is the result that should be reproducible, then it usually is reproducible. And if people don't reproduce it – it is just because 95% of all scientific papers are about new results, they are not about reproducing somebody else's work or negative results. But if I don't feel and instead sort of try to more analyze it. What we have seen over the last couple of, just the last three years, I would say is that we've seen the research community more move towards a situation where it's easier for others to replicate - as you are asked to share much more material. So, when you - let's say I publish something in a nice journal, then often I have the possibility or even the requirements to give supplementary material - that could be data, could be algorithms, could be pointers to code or code libraries, and these days at KTH I'm not even allowed to publish in a journal that is not free to people to read, or at least my article has to be free - sometimes KTH has to pay, for the sort of golden access so anyone on the other side of planet download it free. And this, of course, opens up the space where possible much much [many] more people would like to try and reproduce what I've done or have opinions about it. I think we had another question? [Well, just doing some yoga.] Yea! In order to do this and to answer your question, you have to think about measure - always. A measure can be qualitative or quantitative. A qualitative measure would be it's very cold in this room. It is sort of fuzzy - right? And a quantitative measure would be it is 17.82 Celsius in here right now. But it also sometimes requires mensurability. Mensurability, this beautiful word, is often used negatively, so we talk about immensurability, So if you don't have commensurability it means you have no common measure. So if somebody else wants to know the degrees Fahrenheit (I can't calculate 17.82 in my head with any precision) so - but they are still commensurable, they are still possible to translate from each other. And a person that knows about Celsius usually knows about Fahrenheit maybe about Kelvin. They understand this concept of scale and how you can translate between them. That there is some sort of linearity between these two. But sometimes things are not mensurable. So, if I say it - I start to get you worried - I'm saying this room feels a bit poisonous. You might start worrying about am I being subjected to some sort of gas - an experiment in here. Or is he talking about psychologically - there is some sort of poison? What is he talking about? I can sort of get you nervous. And this concept that I invented about this room is not necessarily commensurable with anything to do with temperature or anything like that. It gets more than fuzzy; it's just strange and weird. And you can't get a grip on it. And our job as scientists and usually also as engineers is to always get a grip on things. So, that is why you are here. Right? You are supposed to have a personality that if you don't have a problem to solve - you invent one. That is supposed to be your nature. And this means that you are always looking for these patterns - like if I don't understand how to measure sure this, I have to find a way. So, I need commensurability. This is a cornerstone of reproducibility.

Slide 16: Boyle's air pump https://en.wikipedia.org/wiki/Air_pump

Sometimes this is hard. This is an old picture of a vacuum pump that Boyle did. And is usually cited as the first example of reproducibility - because many people at the time didn't believe that there was something called vacuum. So he said, "Well you this kind of pump.

How hard can it be, and then you can create a vacuum." And just by looking at this picture, it is a pretty tricky thing to reproduce, but still, people managed. And maybe with a little bit more information, see you can zoom in on some details here. This whole story is on Wikipedia if you are interested.

Slide 17: Completeness

Completeness is simpler to explain. It is about having everything relevant investigated and in enough detail. And this is heavily connected to limitations. And I've already given some people in my group feedback about "Whooo! This is this will be a nice PhD thesis - what you have just described. Unfortunately, you don't have four or five years to complete this project work - so you need some imitations." And it's very hard - it's hard to do something in limited time and resources. I've also warned many people that said, "Oh! We're waiting for more data sets - so we will start with these two datasets, and we are hoping that another 5 data sets will be available." You know, during the course of the work. And that sort of optimism is sometimes justified, but it is very risky if you have a limited time for your work. So, one thing that we often do in science is it is a bit of cheating, but still instead of implementing and documenting something, we just specify it. So, we throw in the specification, and that's also work, of course. That means somebody else can take our specification and then they can implement it. We _would have_ implemented it if we had time, but since this is only a 7.5 HP course. But if you do that - if you spec something - your specification entails if it is to be a good one - that you have to describe the whole work - so the whole thing that you would have done - had you had the time to do it. Then your work given your limitations is complete, which is nice.

Slide 18: Objectivity

Finally, of these four: objectivity. Science is objective; that is why it is good. That is something I've read on the internet. But does it exist? Objectivity (I mean) does it exist? So, is there an objective scientific method? Are there objective scientific results at all? Well, many people don't think so. Many people think that it is all about what that particular inventor had for breakfast that morning, or he (that guy) had an apple in his hand when he got this idea. That other guy wanted a battery in a car, and now he wants it in airplanes and houses - because of this of this and that. It has to do with the personality, and you hear about these entrepreneurs - these fantastic minds - and it's very subjective. Elon Musk thinks that we should do this so ... So, you have to make up your mind yourself about what it means for you to be objective in your work. And maybe think about that if there is something creeping in that's not objective and maybe there is some bias involved. Maybe it's because I'm a very privileged person because I'm a middle-aged Caucasian man in a rich country with fresh air and all that. And that makes me write, like, and do certain things with a higher probability than other people. And in normal life it is good, you know - if we all recognize our privilege this would be a nicer planet. But is in science it is absolutely necessary. And, for instance, in medical journals - always in order to publish your medical journal - you always have to declare your interests. So, if you worked for Pizer ten years ago - you have to say, "Oh! And I worked for Pizer 10 years ago." and then it is up to the reader to say, "Oh! Is he writing about these things because Pizer used to pay him to think such things, or maybe there is bias in there."

Slide 19: The Larger Picture: Philosophy of Science

Everything that I have said so far is part of a larger picture of how you can divide science into like four parts. I already mentioned epistemology, which is things to do with knowledge. What do you know? What can you learn from science? And then methodology - which you all have to worry about - because you have to write these things about - to do with method. For your - your work, you need to describe your goals, your hypotheses, your purpose, and all these things. That's part of your method, your hopefully scientific method. And there is a logic involved. It is about the compiler, for instance, or the interpreter for the language that you used - if you implanted something. Or the way you're thinking about your algorithm, maybe in pseudocode, there is also a certain logic to it. Nothing strange. And then finally the ontology. Which do things come from? How do we define our terms and concepts? What rests on what? And these are things that not only engineers worry about, all scientists have to worry about all four parts of science.

Slide 20: Categories and Types of Knowledge: Ch. 6

Okay, I'm going to skip this part

Slide 21: Performance Metrics in R&D: Ch. 6

Slide 22: Roles of Knowledge Propositions: Ch. 7

Slide 23: Management of R&D Case:Innovation Radar

and move to a quick elaboration of a case, to make things a little bit more concrete. This is a case where I used to lead for four and a half years something called Innovation Radar, which was a part of EIT Digital. It was foresight, so it was strategic advice to EIT Digital about what the future of ICT would be like. And as some of you know very well and all of know by now, EIT Digital is organized as a network between different nodes. So, this was work carried out in Stockholm.

Slide 24: Collaborative Work: The Stockholm Node

This is a picture of the beautiful reactor hall at KTH Campus, where we had some workshops.

Slide 25: Innovation Radar: Two purposes

So, when I did this Innovation Radar thing, me and my team had two purposes. One was to support strategy. We had an overarching aim: We should become the thought leader on ICT in Europe, which meant that something like what MIT had said for the United States about thought leadership. So, to be bold and say, "We should (you know) - if people want to know about ICT in Europe - they come us." And the second purpose was to support the strategy of EIT Digital as a whole by doing a lot of scouting.

Slide 26: Innovation Radar: Tested Modes of Operation

And I did a lot of scouting. We did a lot of scouting. We did four sites. We did - we had online platforms. We had a network of scouts all over the world: in Silicon Valley, Tel Aviv. Australia, India.

Slide 27: Example Radar Visualisation: Smart Energy Systems

And we made these radar pictures - like, what is the future of smart energy systems and we visualized them in various ways. Whenever you do this, there is something called management science, which by the name sounds exactly like its a part of science. Right? It is that piece of the pie. There is physics and then there is management science. But, of course, it is a very different piece of the pie. Management sciences are about how you steer processes? How you make money? How you turn a company into a more efficient company? And all these things. So, of course, it is not physics, but there are some maths in there - which means that in management science, you have to mix the quantitative with the qualitative, and you have to make simplifications. So, you have to talk to people that have very little time - at least they think so themselves. So, they instead of reading a twenty-page report, they say, "Okay, give me one PowerPoint with five bullets Max. That is what I have time to read." So, then you have to invent things like these radar pictures, which is crammed full of information. If you zoom in on this, it's like the closer you are to the center, the nearer you are in time to a certain development. The size of each ball there {is} shows the impact. The color shows that people know it at EIT Digital already or if they don't. And then the number has a description. And this description is linked to a lot of material. So, if you are successful in your report - you also have an example where you could [reduce] a whole lot of information, and you sort of funnel it into one picture. Unfortunately, what I find when I read reports in this course in earlier years, when I review scientific papers for journals (which I do every month), I find that figures are misused. Most figures you can just rip them out, and you won't lose anything. Other figures are full of colors when you don't need color. Or they are unpedagogical in other ways. So, please think about this: If you use a figure, use it to actually send over lots of information to the reader. Again, if you know who your stakeholders this means that you can, you can do this very efficiently if you know who is reading.

Slide 28: Future Networking SolutionsVisualisation

Slide 29: Smart Energy SystemsVisualisation

Slide 30: Smart Energy Systems: Business Potential Analysis

Slide 31: Smart Energy Systems: Strategic Map Example

We also visualized the future in various ways. I am not going to go through this - you can look at them if you're interested.

Slide 32: Example of Tangible OutputInnovation Radar White Paper

Slide 33: Healthcare spending (% of GDP)EIT ICT Labs Countries

Slide 34: Health & wellbeing: Foreseen products from a physical perspective

Slide 35: Innovation Radar Annual Trend Report:T-Labs International Scouting Network

In this case, we published and even print on paper - these ideas about what the future would be like with examples: ultra-fast infrastructures and so forth. These were handed out to people we thought were important to EIT Digital.

Slide 36: Bottom-up Innovation Radar HWB 2013

Slide 37: Innovation Radar: Goals

Again, I just want to give you some examples about how we work towards our goals because this is also relevant for your report. So, we had a total of eight goals here. And again, I won't go through them in detail. You can look at them if you are interested. But we needed to create business intelligence, map the future, and so forth.

Slide 38: Strategy Map in Practice (Old memo)

Now, the funny thing is that if a problem you are solving can be hard or so hard, but if you're really unlucky the problem is "wicked" as we call it. And that means that it's so hard you don't even know where to begin. There is no way to do a model. And the person that gave me this job - he was the chief strategic officer at the time at EIT Digital; at one point, he handed me a memo and said, "This is what I need you to do". This is the act memo. So, he gave me this, and he said, "You are part of something called Innovation Radar or you lead it, and it is part of innovation element, and that is linked to something, and so." And what he felt that he had to do, and he was - he was very good at his job, was if I can make Magnus understand this particular picture in detail, then he knows everything he needs to know in order to meet all of his goals. And this is how the real world works. You get memos like this. And this guy honestly thought that he could convey to me in one hour or something what this picture really says. And some of this would just be amalgamated with everything else that I know, all my talents and interests, and [MUMBLE] and out would come these like these which were measurably valuable to him and to the European taxpayer helping the organization become a thought leader in ICT. So, it was all in here, he felt. Whereas I presented with this problem of understanding this, "Hmmm! Maybe I should see some people, talk to some people in this organization before I start writing things base on these numbers".

Slide 39: Innovation Radar: Goals

So, of course, this memo was turned into all these things that I already mentioned. We tried to measure all these goals in various ways. And out of this came a lot of stuff. And the same when you report your work. You describe the tip of the iceberg. Under that iceberg are the hours when you sat, and you didn't know how to solve the problem, maybe it was an algorithm, maybe it was just that your friend was out chasing Pokemon while you were trying to compile. And most of these problems you can solve by just talking about them.

Slide 40: Innovation Radar: Goals

Slide 41: Foresight Studies

Slide 42: Foresight Technical Reports: Example Output

Slide 43: Experts in Structured Interaction: Networked Foresight

So, one tip, which might be too late for some of you but in good time for others, is that use the other groups to give you feedback - and this is partly formalized in this course through peer review. But I don't mean that. I mean over coffee or whatever. You can even go out and chase Pokemon at the same time as you're actually talking about your experiences, how did you divide the qualitative parts from the quantitative parts and when you did your benchmarking, did you just do it on one machine or did you test several machines, did you assume a normal distribution in this analysis or did you consider it could be a Poisson distribution, and how are you thinking and where did you find this information? skip skip skip skip

Slide 44: Cultural Diversity in Full Effect: Networked Foresight

Slide 45: Value Creation through Networked Foresight: Employment

Slide 46: Foresight Instruments: Good Practices

Slide 47: Peer Review

So, normally we have a break, but Chip tells me I want to. I can just go faster, and then we stop earlier. Are you okay with that? OK. This is great I might fall asleep considering this nine-hour time difference. So, I want to talk about the peer review as a special case of scientists looking at other scientists' work. And, I have to confess there is a bias here. I am fundamentally not a believer in anonymous peer-reviewing. So, whenever I peer review, almost always I throw in my name, and you will know in this course, I guess, I always know who has opinions about your sketch. But what scientists do is they often use- they often submit in a double-blind situation - which means that I don't know who's reviewing my paper and they don't know who wrote the paper because the name my name is not on the top of the paper. And the references that point to my work are deleted. So, all the clues about who I am should be taken away. And that doesn't stop me and others, of course, from sometimes knowing exactly who wrote this paper. And if I'm doing this for a journal, and I do this so maybe 10 different journals, and I am the associate editor also of one journal which is called Eurosurveillance- It is a journal by the European CDC based here in Stockholm. And if I think that all this was written by people that I know, I should tell the journal, and say "I'm not a suitable reviewer for this because there's too much bias and I owe the money so I shouldn't review their paper."

Slide 48:

There is an example in Peter Bock's book, and it's about (you can't read this is too small), but it is two French scientists, they are in the late eighteenth century, they are up on two different hills trying to measure the speed of light. And they do so by having a device which is a lamp, and they have a shutter that they can open and close. And the distance between the two lamps was 2640 meters. And scientist A would open the shutter and at the same time start a stopwatch and then when the other scientist saw the light come on from the other guy because the other guy would have watched when his light came, and he would make his light come on, and he would stop the watch. And they would try and use this method to measure the speed of light. Now, it's not a great idea - for a number of reasons, but the main reason is that, for instance, if you consider athletes in track and field and they have these starting signal that is ready, set, go. You can actually be disqualified if you start too early. Even if you start after the gun has go off. If the distance is too small between the actual bang and your possibility to detect that. So, what you have detected was the guy's finger is starting to pull the trigger or something. And then you run, then was the bank, you still get disqualified. And if you want to measure the speed of light, you can't do by lanterns, and you can't do it by using a method that is completely inappropriate for this. And today, if you go on the internet, you will see a discussion of was Einstein right Was Einstein wrong when he said that nothing could travel faster than the speed of light. So all you have to do is go to YouTube and see lots of lectures about how to properly measure the speed of light and some hilarious examples of people that thought like this. The thing is these two guys went to the local disco afterward and talked about the success of their experience and what they needed was somebody else to say, "Guys, You're not really measuring the speed of light you are measuring how long does it take for a human being 2640 meters to detect that some other guy is opening the shutter of the lamp. Something like that what you are measuring." and that will be the peer reviewer, the one that's raining on your parade.

slide 49: Swedish Medical Research Council Case

And there is an interesting case of peer review, which is from the Swedish Medical Research Council and which turned out to be a very well-read publication. And it's out there on the internet so you can download it for free. But I chose this year not to have you read even though it's only three pages long; I know you a lot of material anyway. But if you're interested is there you can find it for free download it. It was written by two Swedish women Christine Wennerås and Agnes Wold. And what they wanted to do was, they wanted to check if the peer review system was biased or not. And they had a particular bias in mind, they were looking at the gender bias, and they were sort of worried that so few women got grants from a particular grant giver, The Swedish Medical Research Council, and they thought something must be wrong with the system - it's not that something is wrong with these women. There must be something wrong with the system. And they decided to investigate this.

Slide 50: 3 Possible Reasons

So, if now women are less successful than men when it comes to getting grants from the Swedish Medical Research Council - what reasons could there be? Well, they said, "Okay! It could be three reasons. The first reason could be that women are less motivated and career-oriented than men. Okay, another is that women are actually less productive than men, and consequently, their work has less scientific merit. And the third possibility is that they are about the same, but they suffered discrimination because they are women and for no other reason."

Slide 51: Conceptual Model

So, when they wanted to investigate this they - a conceptual model and this might be the ugliest slide you have ever seen, but it's not about its ugliness, again this is something I wrote that down on paper to derive this mode of what they were trying to model with this figure you have from their paper, but you have an applicant had a gender and age and a PhD and a year, and their basic degree, and they would be named in an application. There were n the particular year that these investigators here are looking at; there were fifty-two female applicants and 62 male applications. And this application consisted of a CV, a bibliography, and a research plan. Wow! Recognize that? Now, there was a review - this was a peer review. The peer review would give a score from zero to sixty-four, and the reason it could be so high was the highest you could get was four multiplied by four multiplied by four - sixty-four. So, if you got three, three, three will be 27. And these three scores were broken down into scientific competence, the relevance of the research plan, and the quality of the method. Now, a reviewer or more - one or more would do the reviews, and they were each part of an evaluation committee. They would have a board, and the board would look at the ranking, and the ranking would give the result of who should get a post-doc fellowship grant from the Swedish Medical Research Council. Now, the end result was four women, and sixteen men got these grants. So, it seems that this is sort of skewed you if you consider fifty-two versus sixty-two verses four verses sixteen. So, they got published, this investigation they did in Nature, which is, as I mentioned at the beginning, one of the two best journals in the world. So, they went through the Nature peer reviewing system, and of course, they had to make sure that their method - their own method - was as good as possible in order to to have their results pass this most - this notoriously difficult peer review system of Nature.

Slide 52: Methodology

So, their own hypotheses for their work was that peer reviewers are incapable of judging scientific merit independent of gender. So, if we talk about something like male privilege, then any man that acts in this role being part of the board during these years could not just leave behind the fact that okay I'm a man, so I'm going to look at other men applying for this position in a different way than I look at women. And the method they use was the regression analysis or multiple regression - which means that they had defined parameters and they looked at the scientific competence versus a competence score and they have six ways of measuring scientific productivity which was different from the ones used during this previous slide - these three were scoring only three different things and then multiplying it through. So, what they did was, first of all, they have to get the data. Now, you might think well, this should always be open, right! So you can just ask for them in a country like Sweden - information wants to be free and all that. No, they applied for getting access to the data at the Medical Research Council and their board said, "No, we don't hand out this data for research - it is very sensitive because these peer reviewers they write, it is full of sentiment, it is full of subjective points - it is like a health record for a patient - you can't just hand these out." So, normally a researcher is then [disappointed grunt] "can't get the data what should we do then". But not these two, they went to court and sued the Medical Research Council, and they won. So, the court said, "actually these are official documents, and so you have to handle them to these researchers, and they can't publish them, of course, on the internet or something, but they can use them for their research." And this was sort of; I wouldn't say unheard of, but very unusual that a researcher wants to research something, and in this case takes the Medical Research Council to court. So, that was interesting in its self. Then they had the data. And then, they had to look at this data. What they had to do was read, of course, all the CVs, videography, and research plans, And they had to come up with these six different competence measures. Because what they wanted to say was that these people are looking at the one thing they are measuring one thing, and we want to look at the same applicants but measured through a different system which we feel are fair and free from discrimination. Then we want to compare these two. That is what they did.

Slide 53: Getting the Data

And this was about getting the data.

Slide 54: Applying the Methodology

So, if you look at their conclusions -- hmmm! --- I was looking for a particular quote here. Well, they say things like this, peer reviewer deemed women as particularly deficient in science competence. This was one of the outcomes of their fairly qualitative research.

Slide 55: Assumption

They made an assumption, which I know many people think is very strong, Chip and I have discussed this and other people have discussed this. So, this is not an uncontroversial paper. But still, it was published in Nature. So there is not much I can say about that. They perform multiple regression analysis, and in this analysis, we assume that competence scores are linearly related to their scientific productivity. And then, they constructed six different multiple regressions with one for each of these productivity variables that they had come up with. Now, for those of you that use some sort of sampling - it's very important for you to know the underlying distribution always. So, if it's normal, then you know that everything is Gaussian. You can use the standard deviation and variance- you will hear more things about this in this course. If it is not a normal distribution, then some measures that you want to use - you just cannot use - because it's against the law of statistics and you'll be jumping to conclusions, and your conclusions will not be objective, and correct and complete. So, this means that it's very important to scrutinize this. Okay, the peer reviewers at Nature did this.

Slide 56: Bias?

And what and these two researchers, Wennerås and Wold, concluded in this case, was that here you have the conclusion. So, for female scientists to be awarded the same competence score as a male colleague, they had to exceed his scientific productivity by sixty-four impact points and because they generally talk about ninety-five percent confidence - one standard deviation - this represents approximately three extra papers in Nature or Science - then they have the impact factors 25 and 22, or twenty extra papers in a journal with an impact factor at three. Now in computer science, this would mean top journals- So, what they are saying is that they came to the conclusion that if they assume that there was no bias in the peer-reviewing - if I were to buy one of these positions when I was a post-doc when I finished my

PhD, my female colleague would have to have 20 journal quality extra papers published - in order to have the same chance as me - which is, of course, a very, very, very strong result - indicating that - it is this what you have done here - the female application has to be two point five times more productive than the average male application to receive same competence score as he.

Slide 57: Output from Multiple Regression Models

And if you're interested, you can look at the output from these regression models. I leave it for now. So, what can we learn from this? We can learn a lot. We can learn that sometimes it's very interesting to study bias, sometimes this bias can be measurable if you're a bit - ah! - if you're constructing an innovative, you can come up with an interesting way of measuring things there really hard to measure. There will be people trying to stop you in various ways. And this is something else and more about this in just a minute- that some of you will do work even in all the limitations that come from the outside world on you doing this for a course - there will be people that don't like you to write about the study - the things that you chose to write about. And to give you one silly example from last year - there were - there was one project group working on the system that they thought would immensely improve how you ride the subway and buses and trams in Stockholm. They wanted a fingerprint reader, so instead of having a card - you would just put your finger on there - and that was it. The system would know who you were, and it would check through the ledger system if you have paid or not. This lead to a lot of discussion about ethics and what if someone is really desperate and they off my finger to ride free on the subway. Or can I make a plastic finger that always works, which is sort of the same print as my neighbor whom I really hate. Or shouldn't if always be free for every taxpaying citizen anyway to ride on the subway? Why do you have a system at all? And what happens if you - if you skip paying and that that will be guards taking your fingerprint and this is like a surveillance state and all of that. So, the reaction that the group got was a lot of hostility from the peer reviewing and from the other people in the group. They said, "isn't there something wrong about your hypothesis, what it takes to solve this problem, how important it is and the method you use trying to actually implement" because they seriously thought - both of these two - thought, you know - just install the fingerprint readers a better world will come from this - if you do this. And others might look into, for instance, how to how to improve onion routers like ToR to protect your privacy - so that you can do whatever you want on the internet and the remain undetected. And then other people might say, but then you can do this and that, and that is illegal, and you are safe, and so on.

Slide 58: Daniel Nazer and Elliot Harmon, ‘Stupid Patent of the Month: Elsevier Patents Online Peer Review’, Electronic Frontier Foundation, 31-Aug-2016. [Online]. Available: https://www.eff.org/deeplinks/2016/08/stupid-patent-month-elsevier-patents-online-peer-review.

In this case, when it comes to peer review something weird happened last month - Elsevier, the world's largest - I think publisher- I'm sure that is in this business commercially applied for a patent for online peer review - so they just said, "Okay, this thing called peer review we sort of invented it - we want to be ours and if somebody else wants to do peer-reviewing - like we're doing this course - then you have to have a license" and the EFF's awarded this the special award - the stupid patent of the month- which you can see here. And it says, "Fortunately, by the time the patent actually issued, its claims have been narrowed down significantly" ... "But we still think the patent is stupid, invalid, and an indictment of the system". So, what does this mean? Well, we are in a world now where if I want to publish as a scientist - as a researcher, I have to share my data. So, I use, for instance, a lot of health records it is sensitive data, I cannot share it. So, what can I do? Can I not publish? Well, I have to come up with a way then for others to replicate and validate and maybe even verify my results, by giving them some other way of inspecting that my work is correct. And one thing that I can do is to, for instance, convince peer reviewers of the journal that I sent my results to: okay - I created this mockup data set it has all the same statistical properties of my original data set had, and you can replicate my results using this data set. Now, I share this with you, but I cannot share with you the original data set, because I don't have an ethical permit to do so. My ethical permit says I am responsible for this data is supposed to be on one machine up on the sixth floor, and that machine is not connected to the internet, and I am responsible for putting it in a locked cupboard every Friday afternoon or every day; then I can have this data. Ummm! Another thing I can do is say, "okay, here's what we're taking away everything that makes it possible to identify real people behind this. ". Which is increasingly difficult to do because only a few months ago, there was a paper published on how easy it is to find out who a researcher is actually talking about when they share a database in this way. They were looking at credit card information. They were saying things like: with three uses of a credit card and you have a seventy percent chance of correctly identifying who was behind [it] - who is the owner of this credit card. Any three - so three random uses of a credit card. So, this - this is putting researches into a problematic situation where I cannot tell my graduate students to use my data to publish things - as they run into a problem with their publication saying, "Oh! This journal with these other researchers they require we use open data for applications". But, it's a good world - no thanks to Elsevier, which is trying to use a patent weapon to sort of stop certain ways of doing science together with other people in critical - critical constructive criticism - if I call it. But thanks to this new trend of actually sharing much more data - coming back to the question of an hour ago. So these days, for instance, this summer, I worked on an algorithm together with a colleague of mine at SICS for recognizing emotion expression on human faces. And so, we trained a deep learning network to recognize features of the head position, eye gaze, and things like that. Our work was _considerably_ speed it up by using an open-source pipeline to do - to take input pictures and produce output video through that pipeline. So thank you for sharing that code to some researchers I've never met. And then, the other thing was some researchers in emotion recognition had shared a database of one terabyte of filmed people that was annotated with the emotions - so here is joy starting at six seconds and eight-point two the seconds, and that so of thing. And we can use that to train our neural network - so that when we fed in our new data that we were really interested in learning about then thanks to the training we had done - it turned out that our algorithm could perform a lot than we thought and also there emerged certain interesting things - like the fact that it could be used for recognizing faces, even though we didn't even training it to do that, but it could still have some capacity to say, "here is the subject I've seen before I have seen this woman in an earlier picture." Which is very nice from an AI point of view. So, the world - the research world is getting better - because people are sharing more and reputation comes easier. But for you - for those of you that want to become scientists and I remember those two hands going up - and hopefully, there are more than two of your who want to jump into the world of science, then you have to think about how open can I be with my resources, with things that I'm studying - for my - for my research. In order for me to get published, it's important that it is open.

Finally, I just like to say that for those of you that are in my group I will see you tomorrow, but for those who there are not in my group - if you are interested in AI or data science or epidemiology - Come talk to me about your master's thesis if you like - you have - I always have some something going on, something cooking, so you're free to just send me an email if so. I also spoke to Chip about there are some groups that are being formed where I understand there's one person in your group and one person in my group - you shouldn't be in different groups; so, you have to choose - you have to make up your mind - it is either of us. So, I might be waving goodbye to someone. Chip might be waving goodby to someone. You should really be in the same group. Okay! Thank you very much for your attention and take care. [APPLAUSE]