[Music]

Welcome to the second lecture of the seventh week of the course in machine learning. So this lecture will be about the second theme for this week which are called Interdisciplinary Inspiration. Essentially this lecture doesn't present so much new material, it merely collects together all the parts that have occurred during the course where other disciplines have inspired the work and development in machine learning, in particular but also in artificial intelligence in general. Let's start with what is most important, so artificial intelligence and machine learning are very much dependent on mathematics and statistics, I hope that this message has gone through, I mean in this course I have tried to be on a level but not all the time borrow down into this areas, but I've also said clearly and consistently that when you develop your knowledge in this area, when you go deeper and when you continue if you continue with this area after this course you will under all circumstances need to handle much more mathematics and much more statistics. So let's start with mathematics, so there are a variety of parts of mathematics that come into play, so I mean one important area is the vectors, matrices, linear mappings, with an inner and outer products for those measures of similarity in Vector spaces, how you can differentiate matrices and vectors, chain rule is an important element in certain corner of machine learning, inverses of matrices, least square techniques, Eigen values, Tensors etc. But also geometrical aspects are important so Geometric interpretations of mappings, other things like Hypercube Discriminant functions and so on, and also Optimization techniques furthermore graphs and Digraphs, I guess you have observed that graphs occurs in various corners also. So in a similar fashion statistics is also a cornerstone for this area. So this is a traditional dealt with data collection, data modeling, data analysis, data analysis, and data presentation maybe we haven't really highlighted data collection and data presentation so much in machine learning, but of course when you do a practical project it will be eventually there everybody have to collect data doesn't matter where they you are come from a background where you call yourself just statistian or you come from a background where you called yourself a machine learning scientist, so the core theoretical parts of statistics are of course from the fundamental, mathematical statistics based on probability theory, so all the fundaments there are important. In general machine learning is more dependent on inferential statistics in a sense that statistics which want to draw conclusions on whole populations from the studies of samples while something called descriptive statistics primarily summarizes the samples themselves and don't do not draw further conclusions. So specific areas that have occurred during the course are Markov processes kind of Stochastic processes, Bayesian methods, Monte Carlo methods and also so on. So the influence of mathematics on statistics is not I wouldn't call it just an inspiration, I will call it necessary foundations for the area.

Let's move on now to some other disciplines, first looking at Theoretical Philosophy and Logic. So obviously the classical modes of reasoning inherited from theoretical philosophy logic have been had a strong impact on artificial intelligence in general and machine learning in particular and those for the classical ones, Deduction obviously very important in the inductive logic programming, Induction it's a foundation and general source of inspiration for most parts of machine learning, Abduction as the basis for explanation based learning and backward reasoning in Bayesian networks, and Analogy finally as a basis for case based reasoning and associative memories. So hopefully you already seen these couplings during the course. The couplings between logic they are improving and certain parts of artificial intelligence are also very strong specific examples that has been mentioned during the course of the following, so early programs in artificial intelligence like the Logic Theorist program by Newell and Simon proved theorems from Principia Mathematica. McCulloch and Pitt when they analyzed the capability of neurons for performing logical operation was based on a specific logic notation used by a logician component currently Carnap. Logic programming is based on a specific theory proving technique called SLD resolution. Finally LISP language is based on variant kind of logic calculus called the Lambda Calculus. So I one can continue to count on that there are many techniques in this areas there is a source of inspiration in logic somewhere.

Let's turn now to Linguistics. Probably you will find it more difficult to see the real coupling to what we talked about this course on with respect to linguistics but I went anyway I want to say a few words about this discipline, so actually many aspects of language including learning of language is central to artificial intelligence and actually the theoretical and structural view of language and its major proponent in Noam Chomsky who published his classical works of Syntactic Structures in 1957, as I remember artificial intelligence was defined in 1956. So this view of linguistics a very formal theoretical view of linguistics and very well in hand with the developments in computer science and artificial intelligence during the same period. It also was well aligned with the movement away from behaviorism towards Cognitivism in psychology which will come to in a minute. So finally other linguists like George Lakoff widened the work of Chomsky not only focusing primarily on syntax but also semantics and also highlighting the importance of cultural differences and embodiment. The various approaches in machine learning reflects a long ongoing debate in psychology where the pendulum in the last century has swung between Reductionism and Cognitivism. So Reductionism strives for reducing explanation of all mental behaviour into neuro physiological low level process. So you can easily relate here toward a visual neural network approaches in machine learning. While cognitivism represented by psychologist like Miller, Broadbent and Cherry and Bruner argue for the relevance and existence of an abstract model of Cognition in terms of Symbols, Concepts and logically related inferences. And hopefully you can also easily see there the analogy on relation to symbolic machine learning approaches. So this is clearly the sub symbolic side of the coin and the symbolic side of the coin. So if one look at psychology during the last hundred years the pendulum as I said a swung between these extremes and in between them are various middle standpoints, so if you start with Structuralism with I think which it was a very strong movement to begin being of the 19th century, so actually there in that approach you try to define the simplest components of what of our mind and then put the pieces together to model more complex phenomena of the mind but in this approach is not very empirical actually the evidence was primarily based on introspection on questions to people and there own reflections on their own thinking and about self-reports. So as a reaction to that came Functionalism which was more looking at the functionality or behavior, so try to explain the processes of the mind in terms of the usefulness of the manifestation of the behavior and less theoretical more practical and more purposeful. So that then developed into something more extreme which is kind of well-known Siberian hope (11:21) psychology called Behaviorism, where ministers (11:25) like Watson Skinner, Thorndyke Pablo. Assumes that all behaviors are either reflexes produced by response to certain stimuli or a consequence of that individuals history including especially reinforcement and Punishment in certain situations together with the individual's current motivational state and control stimuli. So the parallel to the perspectives in reinforcement learning is the kind of obvious here. Finally things changed again so we moved now more towards Cognitivism, so it just thought psychology is also a part of psychology which more focus on the global phenomena the holistic parts, so and you will see now when we come to neuro science that also neuroscience has this very complex debate between researchers looking atomic phenomena or more realistic phenomena.

So let's now look at an area which we have touched many times during the course and that's categorization or if you want classification or concept formation. And actually I think it's fair to say that the inspiration for how we think about categorization comes from not only one other discipline but from several, it comes from philosophy, psychology and anthropology combined. So what I want to stress here is kind of two views on categorization. So one view which I call here the classical view of categories, this is very old roots from Aristotle and Greek philosophers but also exemplified by work by later philosophers and psychologist like Bruner. Actually the idea here the main ideas are the following, so idea is categories are arbitrary so typically the viewpoint is that we as humans define the categories it won't primarily based on a language or culture, the context we are in, so there is no underlying restrictions that that we naturally have to follow. Also that categories are defining attributes the features we talked about during the course and the feature value combinations what defines it's certainly the feature value combinations that distinguish category from another. And all members of this category share these attributes and no non-members share them, so there are no overlap between members of a category and the non-members of a category, so the intention which is the set of attributes actually in a descriptive form determines the extension exactly, this means that they define and exactly which these members can be, the members of the category can be. So the member space has no internal structure it's just have an abstract definition, all members are regard as equal and first-class citizens of this which category and also the levels in a hierarchy or may not be in hierarchy can may be a lattice, also at the same status, so the one level is not different from another in such a structure. So as you see this is a very well defined crisp way of defining categories. So actually the alternative which we'll call the Modern or a natural view categories or sometimes it's called prototype theory you will understand why in a minute, so it categories here are in many cases motivated by properties of our sensory system and the world surrounding us. So actually in this approach if you recognize that there may be the model ways that could still be cases for objects where the categories can be defined more in an arbitrary way as in the classical but in many cases it may be so that there are these restrictions physical restrictions of our world and our sensory systems ourselves that actually constrain what is reasonable to do when we get there it's actually then the view here is that one build categories around so called central members or prototypes defined by sharing, they share more attributes with each other members than with non-members. So therefore the membership are kind of graded on based on this kind of typicality and obviously typicality generates a topology of this member space and the borders between categories therefore are fuzzy rather than crisp as in the classical case. Also in this view the levels in a hierarchy or that is kind of different stages where some researchers argue that the middle layers of the hierarchies which are more correspond to everyday things called the basic level, while the more abstract their categories and the more detailed levels equal superordinate and subordinate levels have other properties. So the shift from the classical view to the modern view was kind of triggered by a number of work and actually a lot of these works were based on a very popular topic it's actually when people looked at color terms, color terms what kind of colors do we fancy to use and perceive in different concepts and actually there was a famous study by researcher named Berlin, where he looked at color terms in ninety-eight countries, so actually every culture have different views on this. So if you look back at the course I hope you can see the coupling here so that you can see that some of the learning methods we looked at are still very much influenced by the classical view, while some others like the instance-based learning approach, some kind of some forms of the clustering analysis like the k-means approach for example, are very much inspired by the modern view. So hopefully this explains it's a very natural coupling, I mean these are the two major ways of viewing categories and they are naturally reflective and also in the machine learning.

So let's turn now to neuroscience where the area which is obviously influenced machine learning. A lot so the object of study on the nervous systems animals in general and humans in particular, special focus is also on the brain and as we have talked a lot about the atoms of the nervous systems are neurons and an observation here of course that's important that in the nervous system everything is analog not digital as in the artificial systems. So I wouldn't repeat the terminology we have a terminology here about the parts and aspects of the neuron and what I focus here now actually are two major questions discussed in neuro science of psychology for almost century. So one issue is that to belief that brain functions contribute to specific behaviors are primarily local limited brain areas what's called the principle of Locality contra the belief that large portion of the brain contribute to all kinds of behaviors which is often called Holism. The second issue here is the belief that cognitive models of behavior are just a figment of our imagination and that all that exists is the myriad of atomic neuron activities which is then termed Reductionism and different people have had different standpoint also with respect to whether everything there is the mobile level thing and it's not meaningful to try to model something on a higher level. So the above two big questions will be further elaborated now well by we'll look in more detail on the work by a number of famous neuroscience researchers, we talk about Karl Lashley, we will talk about on Donald Hebb, and we will talk about David Hubel, Wiesel and a few other researchers.

I want to start by saying a few words about the work by Karl Lashley. So Karl Lashley was one of the most influential your scientists of the first part of this 20th century. He started as a student of the father of behaviorism but developed into the most clear scientific proponent for balanced view between Holism and localization. So furthermore Lashley, in spite of being a scrupulous experimentalist seriously questioned the more extreme believes in reductionism. He moved the focus from a multi passive view of the brain primarily triggered by external stimulus. So essentially the idea before that was that the brain kind of sleeps and it only do something when it's triggered, while Lashley promoted a view where you have an almost always active brain doesn't matter when you have internal or external stimuli or not, the brain is always active and it has a central control and Hierarchic control that proactively accommodate to external input, so essentially in the hero here is that brain is active and it's has a central control organization that can and handle the whole and react took to the various input that takes place. So there are few very important concepts that was introduced but by Lashley, so and one of them what is a Equipotentiality by that he meant that large areas of the brain potentially has the possibility to contribute to specific behaviors. In many of the experiments done by Lashley and others at that time, actually people looked at brain injuries and even artificially caused lesions (24:37) of the brain and obviously then studying what was the behavioral effect of that a certain point in the brain deliberately was damaged or was damaged from some natural causes. So this means that as a part of the brain had a problem or was damaged then obviously according to the hypothesis of a quick potentiality, others areas could potentially take over that thought from the beginning had been the major contributions to the game. He also introduced this idea about mass action which has a related meaning, meaning that the consequence of a brain damage is more proportional rather proportional to the amount of damage then exactly where the damage took place and finally he introduced the idea of plasticity and plasticity that means that if one part of the brain is damaged than other parts, then can gradually take over the contribution then making the individual able to evoke the same behavior necessarily before the touch occurred. Lashley also seriously researched the possibilities for sharply localization the manifestation of singular concepts or memories in the brain. And this then relates then to actually be the reflection on whether it's meaningful to talk about, where a specific memory reside for exactly which phenomena in the brain correspond to a specific symbol or concept, and he called this endeavor this search for the Engram and I can say that his conclusion was kind of empirically negative, his conclusion was that essentially it was very fruitless to find this exact evidence as fruitless as the search for the only grain, the reason for that typically in functionality seems to be spread over many areas but the way he expressed this in all his writing was that one was merely as temporary the negative observations from the research indeed, didn't make any very radical standpoint what theoretically could be possible but this means that other researchers who really want to find a graph researchers like Simon and Newell they were rather encouraged by reading Lashley the opposite.

So let's turn to the work of Donald Hebb hope remember him. In 1949 he published his theory claiming that an increase in synaptic efficacy arise this promised presynaptic cells repeated and persistent stimulation of a postsynaptic cell. So this Hebbs theory, Hebbs rule, Hebbs postulate, whatever you want to call it summarized that cells that fire together, wire together, the more they fire together the more they get connected, and essentially one could say then there are two ways this can move, so if two neurons on the other side of a synapse or activate synchronously then the weight of that connection should be increased, but if they are not activated synchronously then the weight of that connection should get decreased. So as Hebb described the overall learning phenomenon of the brain, it was actually a combination I mean can think that the Hebbs series only local and of course it is so Hebbs Rule actually describes what happened in each part so the local learning enabled are directly related to Hebbs law, but also Hebb in his writing emphasized more Holistic learning in the sense that when this I mean what happens in a neuron was most similar and it could happen to me all neurons in parallel actually. So if one considered what would happen in the whole system in his view what was built up what the serial structures or more complex structures performed, so as a whole when reading Hebbs the picture your get is its both the focus or what's happened locally but also how the brain develops more holistically.

So the next pair of researches that we have mentioned during the course are David Hubel and Torsten Wiesel. And actually during the 1950s and 60s they did the experiments that showed actually that specific neurons in the visual cortexes of the cat and monkeys individually responded just to what happened in special regions of the visual field. So these smaller regions of the whole visual field they called receptive fields and what happened in receptive field them primarily triggered locally the specific neurons, but of course the receptive fields will overlap so they are not fully separate and so this whole process of responses of specific neurons to set subsets of stimuli within these fields they referred to as neural tuning. They also hypothesize that there are two kinds of neurons, there are those that handle simpler phenomena in the visual field like things like corners, I mean geometrical things, these neurons that can detect this kind of simplifier phenomena they called simple cells while there were also other neurons that could react to more complex phenomenon occurred in individual field, and they also hypothesis the model where for whole pattern or image recognition tasks there is need to be some model how this is cascaded where these kinds of cells work together in a more or less hierarchical fashions. And actually their work is then one of those examples that the focus again worked towards the locality obviously.

So here is just included one of the slides that we showed earlier when we talked about image recognition actually the current model of more less Human Visual system and I think the main message here is that people believe at this point that we have a pretty clear model of this subsystem.

Finally I want to mention more briefly some other important work in neural science at also to some extent influenced the way we design artificial systems of the same kind. So and also researchers that have different standpoints or contributions in in recording the two questions I raised initially. So Roger Sperry, a researcher that is famous for his work on the two brain hemisphere actually but first one to very clearly observe that the two brain hemispheres have different functionality while the left right are different ,the left a stronger role for language and conceptually oriented task while the right is for more focused on spatial functions as an example. Sperry also studied them just this is a phenomenon because it's not entirely true that the one side of the brain takes care of everything for a specific function map, so even here that can be some plasticity, so even if the left is better on language to some extent, the right also contribute to languages and the randomness of one of the other that can be some plasticity also but still there is domination of one over the other. So some Russians researchers Alexander Luria and others looked also then into the hierarchical organization how different brain regions which were which regions were dominating for a certain kind of thoughts and which were more I would can say subcontractors. And also what they try to study is how this kind of role play between the areas would change over time so for example for a child that could be a certain role play typically when you are doing a more sensory regions dominate over others why when you get older the more planning oriented regions get an upper hand. So essentially the one can say the governance of our thinking change over time in this way. Other researchers looked for example at the relation between simple neural functions and the functionality of the whole organization, but I would say the trick here was that the researchers who did a lot of very little of emotions (36:50) on this they were clever and chose to study very simple organism I mean if you study the humans and more advanced animals it's a very complex, so if you really want to see the relation between a few neurons system then it makes sense to study very simple organs which they did others looked even more on the localization so that's another example then related to what we saw in mission (37:32) so for example there are some famous studies of the song of birds where obviously the ability for singing in a particular way seems to be very localized in birds nervous system. So finally also a kind of famous standpoint that was put forward by an article called Pribram this an analogy between the brain and an hologram so I can say this is the extreme holistic view but in the same sense as a hologram being an image recording where every little piece of the recording can be used to reconstruct the whole image in the same sense every part of the brain contribute to everything, but I assume you already understood that this probably not true there is some balance here between localization and Holism look at the sum of the contributions I have taken up.

So finally something related in neuroscience but actually also related to logic is the work that that has been mentioned that that is considered the starting point of artificial neural networks that's the work by Warren McCulloch and Walter Pitts but actually when that work was done it was not consider computer science it was all considered artificial intelligence, was considered but in neuroscience researcher work together with the Logician and what they try to prove was that the architecture the way they thought the neurons in the brain works could function as an architecture for something that could realize or implement logical operators. So this still fits as a source of inspiration because when this was published in 1943 by the machine learning on artificial intelligence existed and even computer science was an embryo at that time.

So a few things that have been also mentioned let's not forget them everything is not inspiration for neuroscience we also saw that there are some systems we built inspired by genetics and evolution theory. The evolution of computing in general and Genetic algorithm in particular inspired by Darwinian ideas about evolution and the survival of the fittest. So in this models one use these terms you look at populations, so you can read a data set as a population, you are chromosomes which is more like a data item for every position in the chromosome corresponds to a Gene read the same thing as feature, and continuing that this kind of systems are try to mimic the way one can see evolution works. So you have generations of populations and in every cycle they are evaluated with respect to how the fit there by using some Fitness function the fittest subsystems are allowed to reproduce and representing place or either by something called crossover or something kind (41:33) rotation and there is a certain order of its phases. So even genetics and evolution theory has passed some extent inspired working machine learning.

I want to end this lecture by mentioning some inspiration not only from computer science but also from physics and engineering science and I hope you will make have some recollections when I go through them. So for example there are some inspiration from thermodynamics so for example if you remember the information gained measure that we talked about in context of building up this decision tree, one used an entropy measure as the basis for the information gained and actually in interpret measure over the probability of a class membership and this is of course strongly influenced by the concept of entropy in terms of thermodynamics and actually entropy is a measure of molecular disorder so the second law of thermodynamics states that entropy can never decrease if no order is enforced by external influence. Also some ideas from statistical mechanics has been included so the energy function in Hopfield networks is inspired by some models from statistical mechanics called the Ising model and actually in this model consists of discrete variables but in the statistical mechanics case represent magnetic movements, of moments of atomic spins we can have two states but the analogy yeah it's clear. So also you're putting remember in Boltzmann machines and we have some processes clearly inspired by processes in metallurgy where you heat up a material to very high temperature and then slowly cool it by that in shaping that one can more easily reach an optimum state. And finally very clearly in reinforcement learning there are very strong inspiration one comes from control theory operations, analysis and cybernetics I mean one could probably say that this is more than inspiration I mean in the same sense and math, statistics are important for a majority of various of machine learning and theory and really really fundamental to reinforcement learning,

So by that I want to end this lecture thanks for your attention the next week and the course will be the final week and essentially we will focus on the repetition of assignments, related tasks as a rehearsal for the final exam, I think that will be the most important thing the last week but also try to show you some larger examples of applications and some demos thank you.