TRANSCRIPCIÓN Clase Synchronic 01 Advanced Machine Learning Methods

---

Profesor (inicio):

Okay, then, well, first of all, welcome everybody.

Thank you for being here for attending this first session.

Deep learning is like the subject I like the most of all the subjects I am fortunate enough to teach in TechDouan Teray.

And I love deep learning. I mean, I love all the version I've been now teaching—this particular class is going to be the third time. And also, I'm teaching deep learning in undergrad for the students in the program of robotics. So it's deep learning there. And this semester, I will also start teaching deep learning for the masters in computer science, the one that is like research based. This is the master's in… They are very similar in the sense of the program. The masters in computer science is very machine learning oriented, what is the one that is full time and is like the more traditional kind of program.

So yeah, this is my favorite subject. I also, also in the undergrad department, in the undergrad, there is the specialization in AI for undergrads. I also participate in that one. So I really like it. I enjoy a lot having the opportunity of talking about deep learning. It is really challenging to teach this subject because it's the one subject that changes literally every day. Well, it changes in the sense that there are new things coming out basically every day. I mean, since last year probably—since ChatGPT in 2023—even before that, it was a little bit difficult to be up with the pace of deep learning and all the models that were coming back then. But since ChatGPT, all 2023 and 24 have been really, really… it has been evolving at such a pace that it's difficult to follow.

And what we're going to do is to cover all the—I think the first half is going to be all the fundamentals that are going to allow us to understand, to take a paper from the… yeah, from that is coming out now and have a good understanding of it. So you will see the program, the program—we are going to be building the contents every week. This is by design. So in general, I mean, we are going to be covering—the first five weeks is going to be foundations of neural networks. We are going to go behind a little bit of the math and the background that is going to allow us to understand how neural networks learn. We are also going to be covering the fundamental model, the MLP, which is probably the most traditional neural network model.

And then we are going to go through convolutional neural networks, which up to today—even today—is probably the most, not probably, it's, I would say, let’s say arguably, the most successful neural network model in terms of actual applications. Since we are going to talk a little bit of the history today… So, but since 2012 that it became relevant again—it’s not that it was invented in 2012; it had been for over 30 years back then—but in 2012 there is these developments where people start looking at the convolutional neural network. So that’s going to be up to week five.

After that, we are going to have one week that we are going to take kind of a breathing week—we call it a breathing week—that is going to be the first quiz. So that’s going to be a week for you to catch up with all the material that we have and also take the quiz, right?

So after that, we are going to go into the natural language processing realm, and we are going to start with some models that today probably are a little bit being phased out due to the transformer. I’m talking about recurrent neural networks. So we are going to spend a week or two in recurrent neural networks and its variations and how they were really key for the first, like, translator applications back in 2017. We are talking about—this is still 2017; I mean, it’s not that far from now. I mean, any other subject you will be studying models that are… I don’t know, if you come from engineering backgrounds and used to study the fast Fourier transform, which is totally relevant today—it’s an algorithm from the ’70s. If you do machine learning—traditional machine learning—you probably are going to be studying support vector machines, which is still not a bad algorithm or a really useful algorithm today. Tree-based algorithms like random forest—we are talking about algorithms that are from the ’80s, right?

And then we come to deep learning, and we are talking about algorithms that are not that… I mean, they are not that new, but they became relevant, like, fairly recently. Like, I’m talking about recurrent neural networks in 2014. That’s only… I mean, that’s only, like, 10 years ago, which is not… But still, they are being phased out, at least for natural language processing applications. So we are going to study that, and then from there, we are going to introduce a transformer, which is probably the most relevant model in the last years—the model behind, I usually say, “the king,” the transformer model. So we are going to be studying the transformer. And yeah, transformer model—we are going to study, we’re going to code it, or you are going to code it like from scratch, like train the transformer and implement a translator that is going to be a really poor translator, a really bad translator, because we don’t have the compute and the enough big data to do it. But still, the principles are the same.

And then the last weeks, the last two weeks, are the ones that are depending on how we do—how we progress from up to the week number 9, 9 and 10. My intention is to do two things: LLMs and diffusion models, which is the model behind these pretty pictures of beautiful dogs and cats. So we say, “Please draw an astronaut—well, a dog wearing an astronaut suit.” So that’s diffusion models. So we’re going to be doing that by the end of the term.

So it’s a lot of information. My emphasis has always been that if we understand the basics well, the foundations well, then we can go on, because everything else is going to be basically the same principles. It’s just going to be the way… The transformer, even if we are talking about the new transformers—there is this Nemo-tron from NVIDIA this year that’s kind of cool—yeah, but it’s still a transformer-based model in the half-trillion parameters. And then we have other models that are achieving a trillion. Still, the principle of learning is basically the same that it was for neural networks. So my point of view is that if you understand well the principles, we will have good foundations to grasp anything else.

Okay, so just to talk a little bit about the grading policies and all that, you can see in Canvas, so I’m not going to spend time doing that. There’s going to be some activities, there are going to be two midterms. One of the activities, the last activity, I’m just going to mention, is going to be like a small essay that you are going to be writing in teams. And probably that tends to be the most challenging activity, even if it’s the least… It’s the one that is not about coding, it’s the one that is about writing, but it’s like doing—it’s not like—it’s actually doing a literature review. You are going to be reading some papers and then writing really concisely and briefly about the topic you select. It’s kind of interesting because, I mean, if you are really interested in some topic in particular, this is your opportunity to read a lot about that and actually have the pressure of a grading system to read about it.

Other things: we are going to be having sessions every week. Most of the sessions, or about half of the sessions, are going to be optional. So, well, I think in general all the sessions are optional, but still, it’s really nice that you show up. So we are going to be having sessions weekly except for week six, the week of the midterm, but all the other weeks we are going to be having sessions—either in general they are going to be like free-flowing kind of sessions, it’s going to be more like to have questions about doubts about the homework, something you read or heard in the news and you want to talk about. I mean, it’s going to be a lot of talking.

That takes me to my next point: I’m really bad at following the chat, so if you have questions, please interrupt me. Feel free to speak—I think that’s the best way to do it. So if you have a question, I mean, you may raise your hand, or if you want to… If you raise your hand, I will be able to see you, and then I will say, okay, I will try to… Or yet Nalisi is also really good at helping me with those questions. But still, if you can speak rather than typing the question, that would be better, because I don’t… Not always can I pay attention to the chat. So if you can speak, it’s actually appreciated. Feel free to interrupt, feel free to ask any question.

The idea is to… After what I have discovered—or not discovered but reaffirmed—is that you guys have a lot of knowledge and information to share, and it enriches a lot the class if you share what you know. So feel free to ask, feel free to share what you have read, what you have seen in the news, whatever you want to talk about that is related to deep learning. So please, just let’s keep it within the artificial intelligence context, and then please, please feel free to ask or comment about anything.

---

Profesor (leyendo mensaje del chat):

Yeah, so there is also a question in the chat: “Yeah, how do you keep up with all the new AI related coming out?”

Yeah, this is a question I have asked. So the real answer—I mean, the totally honest answer—is that I’m still trying to figure out how to keep up with everything, because really there will be—every day is going to be probably a few papers related to a new LLM or a new… Now that there is language models, everything is LLMs. I think there will be a few papers daily, and it’s difficult to keep up.

Something that helps a lot is blogs—like blogs from… They are very good models—like open models from Llama, and then there’s some other non-open models but still good models, like from DeepMind and Google Research, and then you have Amazon and also Microsoft. They all do usually a paper about the model, but even before the paper or together with the paper, there is a blog that tends to be easier to digest. So I think blogs are really good. It’s a really good way—like blogs from these companies, like the blog about some model from Meta or the blog about Dino and all these models from Meta. It’s really… Some really good models—I really have a lot of admiration for what Meta is doing right now. So… But in general, Google, DeepMind, they all have really good blogs about their models, and they tend to be a little bit easier and faster to read, like shorter than the papers.

Apart from that, there are some really good YouTube channels. I don’t know, I haven’t kept up with the new YouTube channels coming up, but there is—like a traditional one would be “Two Minute Papers.” I haven’t followed it lately, but I’m assuming that it still publishes novel papers. That’s very… They are not three minutes, they are a bit longer than three minutes, but still, I forgot the name of the author of the channel. He does a really good job about summarizing papers. There’s another channel that I forgot the name of the author—it’s Yannick. I haven’t been able to follow up lately, so I’m not… There might be some other channels actually that do that. So it would be a way to… It would be just good to have a look, and then probably you will find some even newer, better channels that do that.

That would be my advice, and still probably not the… There might be other ways to do it, but it’s difficult to keep up. Also, I think that if you understand—like there are some foundational papers, foundational models, and some knowledge that would be considered to be really, really important, that underpins everything. I think that if you understand those foundations, then, and you read, like, some iconic—let’s call them like that—iconic papers on the models coming, then whenever you are ready to apply something newer, I think you will be able to catch up really, really quicker than if you don’t have this previous foundational knowledge.

So I would say something that is really important is to have a very strong background in the foundations, in the understanding of what’s going on behind the scenes.

---

Profesor (retoma la explicación general):

So, okay, so what I have prepared for today—I will share my screen now—my screen is just a little bit of a recap of what’s going on with deep learning in the last few years, I would say. But still, if you have any question and you want to ask something before I start, probably I will ask if there’s any question or anything anyone wants to share, please do feel free. As I said, please feel free to interrupt at any point.

\*(Pequeña pausa.)\*

I hope you can see my screen now.

---

Profesor (sobre la entrega de tareas en inglés):

Yeah, also about the homework, professor, that is like a reminder that the homeworks have to be in English. So if there is some question, because yeah, in the last course we had like that question.

---

Profesor (responde aclaración):

Yeah, yeah, the homework—this is particularly… Okay, the point of the homework is like, when… Yeah, ideally, the comments—many, many things of the homeworks, particularly at the beginning, you’re going to have like a Jupyter notebook that you are going to follow. And the idea is… The key idea of the homework is that you understand the code that is provided, and to show and evaluate that you understand the code, what you are asked to do is to comment, because the code will come without comments. And one activity will be to… In all the activities, you are going to be evaluated by the comments. So the issue here is that please do the comments in English, right? So that’s keep up. So that’s like, yeah, I mean… And if there is any reason for… Because also there might be exceptions. If for any reason you prefer to do them in Spanish, expect to also… Then we can… I think it wouldn’t be an issue for any reason—whatever the reason is that you prefer to do them in Spanish, right? Any other language, definitely not accepted. But yeah, we can speak about, for any reason you…

---

Estudiante (interviene):

Good afternoon, professor.

---

Profesor:

Hello, I hear someone.

---

Estudiante:

Yeah, yeah, so really happy to be here. I really look forward to the contents of this course. But I really want to know—I think that for this to work, we have to be aligned, you as a professor and we as students. So I wanted to ask, what are your expectations from us? Like, at the end of the course, what is your expectation for us to know or do, or the abilities that we should have at that moment?

---

Profesor (responde expectativas):

I think this is tricky, and I don’t think there is a unique answer for that. I would say that… And this is something that is also difficult to evaluate for me, because it is kind of a big group. But I would say that the way you can evaluate yourself is, like, at the end of the course, if you take—let’s say, by the end of the course, I’m sure there’s going to be something like this, I can foretell the future—and by the end of the course, I’m sure that there is going to be Llama 4, or there is going to be Llama 3.5 or whatever; there is going to be a new model that is going to be something we would be talking about, probably not in the class, but you will listen about. Okay, by the end of the course, the idea—and this is if you want to evaluate yourself—if you take the paper of this new model that is coming out, and you understand about 50 percent of the paper—I wouldn’t say 100 percent, because it’s difficult to understand the paper 100 percent, depending on the paper—but say you understand more than 50 percent of the paper, you’re good, you’re good to go. I mean, that would be the idea. I mean, that would be the best way to evaluate yourself if you have obtained the most out of the course.

There might be more specific objectives, like you could say, “Okay, I understand how a neural network learns.” That’s definitely something you should know. I mean, you should know. Depending on the data type that you are going to be analyzing and you want to solve it, you have a problem, you want to use deep learning—okay, you should be able to identify what kind of model to use, depending on the data you have or depending on the data modality. So that’s something that you should be able to do. In general, you should be able to—“Okay, I have a problem for my industry, my work, personal project. Probably I don’t know exactly how to solve it, but I have a good idea of how to start solving it, addressing it,” right? These are the kind of things that you probably should be able to achieve by the end of the semester. Well, not this semester—by the end of the class, because it’s only 10 weeks.

---

Estudiante:

Yep, thank you very much.

---

Profesor:

My pleasure, thanks for the question.

Yeah, but this, what I repeat, is more something that you should be able to evaluate yourself, like those are kind of the things that I would expect you to do. And in general, I’ve noticed that it has happened—I have, after the class, supervised some students doing the final project, and they are doing really well, deep learning–wise. So it’s kind of… I would say that’s the expectation in general.

So still, I repeat, if there is any question, please interrupt me. I’m not going to be looking at chat now, so if there’s anything you would like to ask or share, please feel free to do it.

---

## Historia y evolución de la IA y deep learning

Profesor (comienza con la historia):

So what I want to do now is to do a little bit of the history of—I say artificial intelligence, but really it’s more like neural networks, deep learning, machine learning—a little bit of the perspective of how we go to this point, because I find it really, really interesting. I find the history of deep learning, artificial intelligence, is kind of a really nice story. And so that’s how I like to start any deep learning class: talking a little bit about some events that I think are like really, really important and peculiar, in a way. I mean, like if it hadn’t happened, maybe… I don’t know. So that’s what I’m…

\*(Pausa breve.)\*

Okay, this is me, you know my name, LinkedIn, and that you can connect with me, that’s cool.

The first thing—and I’m going to be going fast in the beginning—I mean, the concept of artificial entities capable of some intelligence—let’s say quote unquote intelligence—is not new. And so these are two examples I found about the oldest references to this kind of artificial entities that display some intelligence. One is Talos in Greek mythology (700 BC) and the other one is the Golem (500–1000 AD). And I mean, I was looking, like, what’s the oldest reference? And this is something I found. There is something—this is still like mythology—but something newer and that is kind of an interesting reference to AI, particularly AI taking over, is the "Rossum’s Universal Robots," which is a play from 1920. And the idea here of the play is that eventually the robots kind of rebel against their human masters. Now, the interesting part here is that the concept of the robot… It’s probably the first time that the term “robot” is used in this play. The difference here with robots that we envision now is that they were still kind of a biological creation, right? So they were still, like, biological entities created by humans, and in the end all the robots rebel, right? So it’s been for a while that we have this kind of concern, I would say… I don’t know if it’s a real concern or not.

There is another one in 1927—this is "Metropolis," another—this was a film, actually—and this is another portrayal about robots and this kind of artificial intelligence, I mean, from the ’20s. So it’s not even… The concept of robot is not that novel. And then we have more modern concepts, like \*“The Terminator,”\* and this movie "Ex Machina". This is more recent, I think this is, like, from 2016–2017, something like that. Has anyone watched this movie “Ex Machina”?

\*(Varios estudiantes dicen que sí.)\*

Profesor:

Yes, yeah. It’s a really good movie. It’s a really good movie particularly because it was advised by a deep learning scientist—by, I forgot the name, but it was a deep learning scientist that advised the movie—so it’s really accurate in the terminology that they use. I mean, it’s still science fiction, but the terminology they use is really accurate. So advised by a real scientist. I’m trying to put the gallery view here… If you can, if you cannot, there’s no problem. If you can turn your cameras on, that would be nice—I mean, that’s always appreciated. If for any reason you can’t, there’s no problem, I understand as well. But so it’s all right.

Okay, so “Ex Machina,” a more modern movie, really good movie. If you haven’t seen it, I think it’s interesting.

So that’s science fiction. So how did we get, like, more to the point that we are now, right, in terms of ciencia—like, how did we get to this point in deep learning? It’s not new. One of the first references to the concept of an artificial neuron is in 1943 by McCulloch and Pitts, and they presented the model of an artificial neuron that was based on an on/off state, so that it would be connecting to other neurons whenever it received some on state, and then it would transmit another on state. So something that you will notice, particularly in these years, is that the people working in deep learning—or I shouldn’t say deep learning, I should say artificial intelligence or this concept of artificial neurons, neural networks—were either from a biological background (como neurólogos) or matemáticos. Basically they were the people working on this. And in this case, McCulloch y Pitts, they were in the biological background. So they were modeling neurons in the terms of on/off states.

Then we have, like, in 1949, we have this concept, which is really important, because first we have, “Okay, artificial neurons.” And then in ’49, Donald Hebb presenta el concepto de una neurona artificial capaz de ajustar la fuerza de las conexiones. This aligns very well with the concept of how synapses are happening, how we are receiving—how biological neurons are receiving—connections from other neurons, and depending on the aggregated sum of all the incoming connections, the output is going to be propagated or not. So the neuron might have some inhibitory action or excitatory action. So that has to do with the adjustable connections. If the connections are kind of high, let’s say, more likely there is going to be some excitatory action, and the action potential is going to be transmitted to the next neuron.

Then, interestingly, in 1950, Marvin Minsky builds the first neural network computer. And back then, we have to think that a neural network, if it was going to be implemented, it was not going to be coded, right? It was going to be built. So he builds the first neural network. And then also, he is the one who, you could say, “killed” the neural network research in the late ’60s. So interestingly, in 1950, he’s still believing in neural networks.

And then probably you have heard of this, Alan Turing, in 1950 also, he presents the paper that is called "Computing Machinery and Intelligence". It’s the paper that presents so many concepts. I mean, at least for the first time, he presents concepts that are really relevant today. Probably the most known one is the concept of the Turing test. Have you all heard about the Turing test?

\*(Alguien responde que sí, que es el que identifica si estás hablando con humano o computadora.)\*

Profesor:

Kind of, yeah. Is anyone else that wants to say something about the Turing test?

\*(Otro estudiante: “It’s the ability of the machine to think like a human.” Otro dice: “When you speak with a machine… no difference.”)\*

Profesor:

Exactly. And it was not called the Turing test—it was called the “imitation game.” But then, I mean, I think it would be like kind of… I don’t know many people that name something after himself, so Alan Turing wouldn’t call the paper “The Turing Test.” The paper was called “The Imitation Game,” and that’s why the name of the movie \*"The Imitation Game"\* comes from. So the name was the imitation game, and it was exactly that: it was like you had a human interacting, asking questions, and receiving written answers, and he didn’t know—this person didn’t know—if the interaction was with a human or with a computer. And if the person couldn’t distinguish if the answer was coming from a person or the answer was coming from a computer, then you would say that the computer was deceiving the human. And then it would pass the Turing test, basically. But basically that’s what the imitation game was about, and that’s what became known as the Turing test.

Profesor (reflexiona si el Turing test se superó hoy en día):

What do you think about now, like if you were… Like, in terms of the original paper, as the test was presented, as this imitation game, what do you think—has it been achieved? Like, is the Turing test already obsolete? I don’t know, or is it… If you repeat the experiment that Alan Turing did in the ’50s, which is, “Okay, I’m going to ask a question, and I’m going to receive a written answer, and if I cannot distinguish if the written answer is coming from a human or from a computer, then I would say that the computer is deceiving me,” and then, hence, the Turing test would be passed. What about for today’s standards? I mean, if we repeat that test, what do you think?

\*(Estudiantes opinan que sí, que ya con LLMs un humano no distingue. Se menciona que GPT imita muy bien.)\*

Profesor:

Yeah, absolutely. Yeah, yeah. And the thing is that, if we base the Turing test as it was—I mean, if we repeat the experiment as it was done in the 1950s—probably it would be… I mean, it would already be achieved, right? I mean, actually if it’s only—because also, remember, I mean, the Turing test was in written form, so it was asking, and you would only receive the text, the text. And if you couldn’t notice the difference between a human and a computer, then you would say that the computer is deceiving you, and so if we repeat that…

\*(Alguien en el grupo dice algo sobre “sí, ese es el objetivo de los LLMs.”)\*

Profesor:

Absolutely. Actually, I think it’s more current than ever. The okay—why? Because all the GPTs and all that stuff, that now we can get that kind of answers… yeah, I mean… And the thing is that, yeah, and I agree, because I think, and I would say that most people agree, that if we evaluated the Turing test with the standards that it was originally proposed, I mean, with those standards of the 1950s, I mean, it’s over. I mean, I don’t think we would be very good at recognizing if the answer is coming from ChatGPT or coming from a human if it’s only written. But what has happened throughout time is that as soon as a new achievement, a new milestone, is achieved in AI, it’s like, “Okay, is this a Turing test?” And there is, like, arguments against it. And I think it’s never going to be like—until we achieve, like, a real—if that ever happens in our lifetime—this concept of artificial general intelligence, or advanced artificial intelligence, whatever you want to call it… until that happens, I think people are not going to be satisfied. And the concept of the Turing test is just like, okay, it’s nice to have, but I don’t think it’s that relevant in the sense that as new milestones are achieved, we will argue something against it—at least that’s what’s going on until today.

\*(Se menciona un “assembly test” a modo de broma.)\*

Profesor:

Yeah, yeah, yeah, that’s right. If it can do that in assembly, probably it’s a computer, not a human, but still that’s like the anti-Turing test, isn’t it?

\*(El profesor pasa a otro tema.)\*

Profesor (retoma)

So some of the concepts that came in this time, from this paper, is precisely the concept of machine learning, the concept of genetic algorithms y reinforcement learning. They are presented, I think, for the very first time in that paper in 1950, from Alan Turing. So the question was if machines can think, and then he proposed the imitation game, right?

---

Dartmouth, 1956, y primer invierno de la IA

Profesor:

This is a little bit more of the… This is a test: a computer passes the test if a human interrogator, after posing some written questions, cannot tell whether the written responses come from a person or from a computer. So in that sense, I would say that this is already… We achieved that. We passed the Turing test. So as I said, as new milestones are achieved, the Turing test is just like… it changes; it’s being adjusted.

So something really important—and this is another event that I think is something that we should bear in mind when we are talking about how AI came to be—in the summer of 1956, there were these brilliant people—like I have mentioned before, Marvin Minsky, John McCarthy, Claude Shannon, and Nathaniel Rochester. Particularly, you might recognize the name of Marvin Minsky. If you come from an engineering background, like electrical engineering, you might recognize the name of Claude Shannon. Does anyone know what Claude Shannon is famous for?

\*(Responden que es el del teorema de Shannon, muestreo de señales, etc.)\*

Profesor:

Yep, exactly, you have to sample a signal at twice the maximum frequency contained in that signal in order to be able to reconstruct the signal fully. He’s also known as the father of information theory. Claude Shannon, so probably more famous for that, not for his AI contributions, but still.

So these four people, really clever people, really geniuses, they said, “Okay, the problem of AI is kind of… okay, making a computer. Computers are now super powerful”—I mean, it’s 1956—“computers are really powerful, so we can build a computer. These guys, Turing, showed that they can solve these cryptographic messages, so if we, people like us, as clever as us, get together for a couple of months, for sure we can solve the problem of artificial intelligence,” right? And basically that’s what they proposed. They get money for that, and they organize the Dartmouth Summit in 1956. So they get together with another 10 people that are all really clever people, and they are going to solve AI in a couple of months. John McCarthy, by the way, is the one who comes with the term “artificial intelligence.” And it was in this summit, right?

So, as we all can guess, they didn’t achieve their objective, and they still said, “Okay, it’s going to take probably a couple of years, but it’s going to be done soon,” right? And even so… I mean, they definitely didn’t solve the problem of AI—like they didn’t achieve that a computer actually does whatever we call “think like a human.” They didn’t achieve that. But there are some important milestones from the time, like from those years. You can have… There is a checkers algorithm that was a significant milestone, the Lisp programming language—the functional language called Lisp—was invented back then as well, by John McCarthy. There are some important milestones. I would say that one of the most important ones is the concept of the perceptron by Rosenblatt in 1957. The perceptron, as we will see, is the foundational artificial neural network—it’s the artificial neuron, not neural network, the foundation for the artificial neural network. But it’s the neuron, the artificial neuron as we know them today: one neuron that receives inputs, and we are multiplying the inputs by certain weights. So yeah, let me… I’m probably going to go back to the perceptron because it’s a really remarkable concept. I mean, it’s the first time that someone models an artificial neuron as a… it’s just a linear operation, it’s a dot product. We have different inputs coming into the neuron, we multiply each of the inputs by a different weight, we sum all the weights, and then we get the output of the neuron. That’s the perceptron, presented in 1957 by Rosenblatt, and that’s the foundation of neural networks even today. That’s the artificial neuron that we still use today. So it’s a really important concept in 1957. If I’m not wrong, I think Rosenblatt passed in the ’60s, so he didn’t get a chance to do a lot of research in neural networks, but he presented the concept of the perceptron, which is really, really important.

The ’60s is a little bit what precedes the first winter of AI. It’s when, okay, people for over a decade have been promising that they can solve intelligence very soon—so it’s going to be next year, but probably… okay, next year comes, and “It’s going to be next year.” It’s probably like Elon Musk saying that autonomous, fully autonomous driving cars are going to be in 2021 or something like that, and still not happening. Something even probably more… I would say something similar was happening: they were overpromising and underdelivering. But the difference is that they were not millionaires, they needed money from government to do the research, and the government was like, “Okay, we’ve been giving you money, guys, and you’re still promising things that we are not achieving. So yeah, I think we’re not going to give you more money—so not for AI.” And that’s one of the first winters of AI we have been. So-called, we have had two winters in artificial intelligence, which are these periods when the governments stopped funding research in AI due to lack of results.

Also, something really important that happens in 1969—and I was telling you that Minsky was the one who built the first neural network computer—but he is also the one that published the book "Perceptrons," en 1969. This book shows that a perceptron cannot solve complex problems—in particular, it shows that a perceptron cannot solve an XOR, an exclusive OR, like this very basic, simple logic function cannot be solved with a perceptron. And because of that, there is an agreement—well, today it’s seen as an agreement—to think that there was a misunderstanding in the artificial intelligence community that made them assume that, “Okay, if the perceptron cannot solve such a simple function, then neural networks are worthless. I mean, they are not going to work for anything. They are not going to solve the problems. So AI is worth following; neural networks are not. So don’t follow neural networks.” And so, on top of having a winter in AI in general, 1969 with this book, the “Perceptrons” by Minsky y Papert, kind of, in a way, I wouldn’t say kills, but hinders the research in neural networks in particular, which is a misunderstanding because they show that the perceptron was not capable of solving this problem. They didn’t show that grouping many perceptrons, both in parallel and sequentially—which is basically a neural network—wouldn’t solve it. But the community interpreted or assumed that this was extended a neural networks. So not many people continued working on neural networks after this, except for the people who kept working on neural networks. So that’s when the first winter came.

So something to bear in mind is that the ideas and the algorithms back then, they were really brilliant. The problem, in part, was that the computational power was very limited. I mean, the general-purpose computer was not available back then, so it was not like they could just test any idea they had, code it in Python, and see the result. So in part, I think the problem of computation was the limitation. There was still some… I said before, the Lisp language… The concept of garbage collection was also invented back then.

Something that happened, and actually is worth mentioning, is that from the late ’60s, ’70s, even ’80s, given that neural networks were not that popular, the AI research that was carried out was mainly focused on using what we now call expert systems, which is these systems based on rules. Y este es el meme famoso que dice que la IA es puro “if-else, if-else, if-else.” That’s kind of an expert system. So it’s based on rules, when you have a group of experts in the domain of the problem you want to solve, and then you have a group of experts in computer science that are going to extract the knowledge from the expert of the domain—digamos medicina—and they are going to code it. You may imagine that the amount of rules that you might need to code will grow probably really large very quickly. A very simple example: the canonical example of machine learning recognizing a cat from a dog. I mean, we could try to write a program that does it, like rule-based, but eventually we are going to come to a point that we cannot just address all the differences, the possible cases. That was the limitation of expert systems. Yet expert systems were very popular in the ’80s, they were very successful.

\*(El profesor cuenta una anécdota personal en Sensata con sistemas expertos…)\*

…So still, the process of controlling that bending of the metal… was done with an expert system, and I can say that that expert system was running still successfully… This was 2016. So they were successful, and they stayed for a long time. Nonetheless, they were kind of complex, not anyone could code it, and also they were really bad at handling data that was not within the data that was coded in the rules.

Profesor:

So probably the most famous expert system is Deep Blue. You might have heard of it. Deep Blue was this IBM system that beat Garry Kasparov in 1997. That was the first computer AI that was capable of beating the world champion of chess. So that was a really, really impressive remark, 1997. But still, it was a computer that was trained by a lot of computer experts in combination with grandmasters. That was one of the complaints of Garry Kasparov: that Deep Blue was capable of studying all his matches, but Kasparov didn’t have access to any match of Deep Blue because there were none.

En fin.

So basically, just a summary: ’43, artificial neural networks; ’57, the perceptron; ’69, “Perceptrons”—we don’t like them, they don’t work. That kills the neural network research. But still, there are people who are still working in neural networks.

---

Resurgir en los ‘80s y segundo invierno de la IA

Profesor:

And in the ’80s, the backpropagation algorithm, which is the very same algorithm that is used to train neural networks today—like LLMs are trained using some variation of the backprop algorithm—that was invented, or it was known, from the ’70s, but in the ’80s fue cuando se usó para entrenar satisfactoriamente la primera red neuronal, 1986, Geoffrey Hinton, the guy that won the Nobel Prize this year—yeah, that guy—1986, together with some other people, they wrote the paper that shows how you can use backprop to train successfully neural networks.

1989, another guy, Yann LeCun, he presents the convolutional neural network. The convolutional neural network basically was an implementation of a prior model called the neocognitron from the late ’70s. Basically it’s the same model, but Yann LeCun actually managed to show that the convolutional neural network can be trained using the backpropagation from 1986. So combine backprop with the concept of the neocognitron, we get the CNN. And in ’88–’89, Yann LeCun manages to get the first application of a CNN to recognize handwritten digits. That’s probably the first successful application of neural networks. In the ’90s, this system is used by the postal system in the US to recognize addresses in letters, to recognize the digits in the letters, and also by ATMs to recognize checks, digits in checks. This is the early ’90s, late ’80s. Also one of the contributions from this time is the MNIST dataset, que se vuelve el “hello world” de las redes neuronales.

Contributions like the RNNs (recurrent neural networks) y LSTM también vienen de papers de 1997 (Hochreiter y Schmidhuber), y un par de años después. Básicamente la misma LSTM que se usó en 2016 para Google Translator venía de esa época. So 30 años de por medio.

Igual, no había datos suficientes ni potencia de cómputo para aprovecharlo. So there is this kind of the second winter, que son los años 90. En esa época, no había mucha investigación en IA, los sistemas expertos ya no estaban tan de moda, etc.

Entonces, la gente dice: “Queremos investigar, pero el gobierno no suelta dinero.” Así que alguien tuvo la idea de decir: “No hago AI, hago machine learning.” Y en los ’90s aparece el término de machine learning, y surgieron SVM, random forest, etcétera.

Después, en 2006, el término “deep learning” aparece con Geoffrey Hinton, restricted Boltzmann machines, etc.

Luego vienen los milestones importantes: 2009 y 2012, ImageNet y AlexNet.

---

Profesor (menciona SVM, RF, etc.):

This is what I was telling you, SVMs in the ’90s, decision trees in the ’80s, random forests in the ’90s, neural networks y backprop, etc., etc.

---

ImageNet y AlexNet (2009–2012)

Profesor:

So I mentioned 2009, y digo que es un milestone súper importante. Algo que deberíamos recordar. Fue cuando Fei-Fei Li decidió que se necesitaba un dataset a lo grande, porque en 2008 la mayoría de artículos de computer vision trabajaban con datasets chiquitos, de unos miles de imágenes. Se hacía un gran trabajo de “descriptores” (histogramas de gradientes, SVM).

Fei-Fei Li lanza la idea de ImageNet, un dataset con ~14 millones de imágenes de internet, clasificadas en ~20,000 categorías. Anotar 14 millones de imágenes de forma manual fue una locura. Contrató Amazon Mechanical Turk. Así que en 2010 lanza la competencia ILSVRC (ImageNet Large Scale Visual Recognition Challenge).

Cada año (2010, 2011) se presentan investigadores. Las cifras de error andaban en 28%, 25%. Pero en 2012 llega un modelo que da 15% de error, algo sorprendente porque el 2º lugar andaba en 24–25%. Ese modelo bajó 10% de golpe. Se llamó AlexNet.

Profesor (explica AlexNet):

AlexNet es una red neuronal convolucional, que en esencia es el mismo modelo de los 80s (CNN de LeCun), pero entrenado con un dataset grande y con GPU.

Ese proyecto lo lideraron tres personas:

- Alex Krizhevsky (por eso AlexNet)

- Ilya Sutskever

- Geoffrey Hinton

Ilya era estudiante de doc de Hinton. Alex era estudiante de máster. Hinton era profesor. Ilya propuso entrenar CNNs en GPUs, y Alex era un gran programador que lo codificó en C++ y CUDA. Entrenaron por 2 semanas en la casa de los papás de Alex. Presentan en 2012 la competencia y ganan. Ese momento es un parteaguas.

A partir de 2012, todos los ganadores en ImageNet usan CNN hasta 2015, cuando ResNet reduce el error por debajo del humano (~5%). Andrew Karpathy fue la persona que clasificó manualmente un millón de imágenes, logrando ~5% de error.

Profesor (anécdota Hinton y Google):

Luego Google se interesa, compra la mini “empresa” DNN Research LLC (fundada por Hinton, Ilya, Alex). Subastan la empresa a Microsoft, Baidu, Google. A ~40 millones. Microsoft se sale, Baidu sube la puja, pero Hinton prefería Google. Venden ~40 M, se van a Google Brain como interns. Hinton: “el intern más viejo.” Ilya y Alex se fueron a Google, trabajaron en TensorFlow, etc., hasta que Ilya se va a fundar OpenAI y Alex se retira.

Ese suceso es como el inicio de la revolución del deep learning que vivimos ahora.

---

Profesor:

So from there, we got 2012–2015, la era de los CNN dominando ImageNet. Luego en 2015, ResNet vence el error humano. Se soluciona ImageNet.

Cuando empecé a enseñar (2019–2020), hablábamos de AlphaGo. “Si no han visto el documental de AlphaGo, véanlo en YouTube, es increíble.” Luego AlphaFold, etc.

Profesor (menciona otros hitos):

- AlphaGo (2016, DeepMind)

- AlphaFold (DeepMind, 2018 la 1ª versión)

- Nueva versión 2020, gana la competencia CASP, predice estructura 3D de proteínas…

- [El profesor menciona que el Nobel de Química 2023 incluyó a Demis Hassabis por AlphaFold, etc.]

Se sigue con Baidu, Tesla, autopilot, etc. Y así llegamos a GPT, BERT, ChatGPT, DALL·E, difusores, etc.

---

Profesor (conclusión de la historia):

And yeah, kind of that’s the way we get to this point. I find it really, really amazing how we came through the path.

Up to this point, is there any question?

\*(No hay preguntas.)\*

Cool. So just to end the lecture today:

IA vs ML vs Deep Learning

Profesor:

You will probably hear or see somewhere the term “GOFAI,” “Good Old-Fashioned Artificial Intelligence,” that’s the kind of expert-systems AI, that’s the kind of models based on rules, etc. Then within that, all this universe of AI, one subset is machine learning, and within machine learning, we have deep learning. Because it used to be the case that neural networks were taught as un modelo más de ML, con 3 o 4 capas, pero hoy día hablamos de redes de cientos o miles de capas.

We are going to be working just in this little subset, deep learning.

We are not going to be using that much of machine learning except for the fact that neural networks are a part of ML. But en general, machine learning requiere más feature engineering. Deep learning es más end-to-end. Y lo nuestro será supervisado.

So that’s what we’re going to be doing: neural networks, supervised learning, y en 10 semanas desde lo básico hasta transformadores y un poco de LLM y diffusion.

Listo, hasta aquí llegamos.

---

Profesor:

I think this is going to be the point where I’m going to stop. There are some other slides, but that’s going to be covered in the tutorials for the week. So I’m not going to spend more time on that. I don’t know if there’s any question or anything you would like to comment.

\*(Pausa.)\*

---

Estudiante (pregunta frecuencia de clases):

Just a question, professor. How often are we going to meet in live class?

---

Profesor:

Once a week, yeah. We are going to meet weekly. As I said at the beginning, the sessions are optional; they are going to be recorded in case you cannot attend. But still, we are going to be meeting once a week. Most of the sessions are going to be like office hours, so that we can comment on questions you may have about the homework, questions about… you may have about anything, many things. Sometimes people come with papers that they read, and I have no idea, so it’s going to be super cool, yeah, just to share whatever you are doing related to deep learning—except for week six that we are not going to meet, then we are going to be meeting every week.

---

Estudiante:

Okay, thank you very much. I really enjoyed this, thank you.

---

Profesor (otro estudiante pide cambio de horario a 6 p.m. en vez de 5:30):

Let me check with… but I would say it’s not an issue…

(Se discute y se propone pasar la clase a las 6 p.m. Aclara que la próxima semana viaja y a lo mejor se mueve el horario a 8 p.m. o viernes. Se hará anuncio en Canvas.)

---

Estudiante (pregunta sobre GPU y Colab):

For this class, are we going to need, like, a super professional version of Colab or something?

---

Profesor:

No, no, no, no, no, no. I mean, everything we are going to do is, like, the most intensive training we are going to do is the translator, and still we are not going to be evaluating on the tran… You are not going to beat ChatGPT or Google translator or anything. The idea is just to understand the principles, so it’s going to be a poor translator, but still the principle is the same. So probably that’s the most complex. And then training in Colab for 30 minutes is going to be okay.

So everything is going to be enough with Colab. Still, there are some other platforms that I think are better than Colab that are free as well, so you might want to have a look at… there is Lightning AI… Kaggle also is a good platform for GPUs… someone mentions Deepnote, etc.

---

Otro estudiante:

Is it enough to work with the free version of Colab…?

---

Profesor:

No, everything is simple enough in terms of compute, so the free version of Colab is going to be enough.

So that’s going to be enough. The idea is that since we are going to be implementing, like, fundamental stuff, we are not going to be training the next version of ChatGPT. We just want to understand the principle. If we get a poor model, that’s fine, as long as we see how it works.

---

Profesor (sobre fecha de tareas):

So next week we are going to be… The homeworks are going to be open every Tuesday—activities that you have to… So every activity, we are going to be opening the activity, and you will have two weeks to complete the activity. So it’s going to be from Tuesday till Monday midnight, not the next week, but two weeks after. So Tuesday… And we’re going to have five activities, if I’m not wrong. So you will have… there will be activity one week, just one week…

Many of the activities are going to be, you are going to be provided with the code, and the activity is understanding the code. So there are tutorial videos, tutorials that might help you. So one of the things you are going to be graded on when you are given code is to comment the code very carefully. Like, do a docstring specifying inputs, outputs, etc. Those comments should be in English. If for any reason you want to do Spanish, let us know so we can tell the grader not to penalize.

Why in English? Because it’s easier to share on GitHub, etc.

---

Profesor (cierre):

So super, so thank you very much everyone for showing up. We’ll see you next week, and if there’s any question, just please send us an email, and we’ll try to answer as soon as we can, right?

\*(Varios estudiantes: “Thank you very much. Bye.”)\*

---

Fin de la clase.

---