short paper

"When Hacking Becomes Easy: Teaching Python In 2025"

I'm going to talk about my experience teaching programming to students who all use AI tools.

Most recently, this summer, I taught an intermediate level programming course titled "How To Build A Bot", which was about learning how to automate processes with the Python programming language. For those who don't know, bots are applications that interact with webpages in autonomous ways, like automatically downloading data from webpages or posting to social media sites. Over the semester, which ended last Monday, students built various "bots" that did different things.

SLIDE https://github.com/aliceaviggiani/map-bot https://github.com/petewise9/eBay_Scraper/

For example, one bot checked ebay every day for new listings of particular pokemon cards, and saved those listings to a spreadsheet; another bot posted images and provenance information of rare maps on instagram.

What's impressive is that all of my students came to this class with little to no experience with programming—and they all built things that they wouldn't have been able to build two or three years ago. From starting almost at zero, they left the course with functional applications that did things in the world. They were able to do this for one reason: because they had access to free AI tools.

What most of them found useful about AI tools were the debugging capabilities, to toubleshoot and fix their code. In that sense, errors that would have previously taken hours or days to resolve could be resolved in seconds.

Although that was also a double-edged sword. The suggested fixes didn't always work, and when they did work, they often led to more errors down the road, or to convoluted looking code that takes more steps than necessary to fix the problem.

One of my students, who was totally new to programming, described his experience interacting with an AI bot as if he was trying to convince or guide it toward a specific conclusion. He would say things like, "It's coming around", and "Its almost there".

In my head, I got the image of the Hulk trying to sew a button.

SLIDE hulk sewing from black-forest-labs / FLUX.1-dev

You have something super powerful, and it's attempting to perform a very delicate task.

The good news seems to be that this lowers the barrier of entry significantly. But I want to make the point, perhaps controversially, that maybe it's not a great thing that programming is more accessible.

Perhaps, people should not be able to build just anything with no prior experience of programming. Not because they aren't genuinely interested in programming (though I think that is important) but because we should have some limits on what we can make. Creating should not be so easy.

And the reason is that, even though programming applications exist on computer screens, operating seemingly independantly from material constraints, these things are very much tied to physical components like hardware chips and data centers, as well as live, human components like data cleaners and labellers, and of course, content creators in the first place.

And for every single one of those points that I just mentioned, AI companies are extracting value and labor without proper compensation. Not only that, where it concerns the physical materials, they are doing so to the effect of massive ecological harm. I'm not going to go into details, but in the global south, there are instances in Congo, Kenya, Thailand, and other places where water and earth is now toxic, creating health problems, destroying crops, and forcing the relocation of communities. And if people think this is limited to the global south, pay attention to what is going on in Tennessee right now, over the past several weeks, where Elon Musk has built a new (and unpermitted) data center.

While there's a big stack of exploitation operating out of view from our screens, those who are in charge of the technology, who are leading these companies, seem to always speak about AI in terms of abundance. There are so many clips of Sam Altman going glassy eyed as he revels over the possibility that every human will have access to their own personalized "intelligence."

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Here's one example of the kind of language he uses:

If you think about how different the world can be, not only when every
person has... ChatGPT... but next they have the world's best chief of
staff. And then after that, every person has a company of 20 or 50
experts that can work super well together. And then after that,
everybody has a company of 10,000 experts in every field that can work
super well together. And if someone wants to go focus on curing
disease, they can do that. And if someone wants to focus on making
great art, they can do that.
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To this prospect, I say no. We don't need "intelligence" to create things in order to have a world of abundance. We don't need it, because we have it already. The world is here, and it's abundant.

What we actually need is to slow down and think about how to make that existing abundance accessible to the most amount of people possible.

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And toward thatcd  idea, I'll end with a project from one of my
students. This project uses AI tools to build something
reflextive and analytical, rather than productive or profitable.
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SLIDE
https://github.com/jfung53/mensmagbot

The project is an image generator generates a text snippet based on content about masculinity. Basically, it scrapes websites that are intended toward a male audience, like GQ and Mens' Health, and uses that dataset to train an AI model to generate text. She uses prompts like

SLIDE masculinity prompts

Then, she uses prompts like ...

#+begin_quote
"Men can be",
"Modern men are",
"Masculinity can be",
"Every man should",
"Any guy would",
"Real men",
"Male friendship is",
"Manhood is",
"Being a father means",
"Being a gentleman means"
#+end_quote

And she gets results like:

SENTENCES

I think work like this is super useful, especially considering the lack of attention masculinity by itself gets in cultural studies contexts.

(For example, while there is "womens' studies", "queer studies", "asian studies", "black studies", there is no "mens studies". And although some people might scoff and say most fields implicitly center mens' perspectives, and while that may be true, that is all the more reason why mens' studies should can examine this in isolation).

Coming back to this project --- this is an example that doesn't build just to produce, but builds for the sake of being analytical. It adds a new kind of knowledge to the world, not just another product or tool.

Thank you.

long paper

panel proposal: What Happens When "Hacking" Becomes Easy? Teaching Python in 2025

questions from proposal:

- when a tool automates a task (e.g., data cleaning), users may not notice its assumptions or limitations, leading to overly simplistic interpretations of complex phenomena.
  - there is value in slowing down, there is immense richery in the close and detailed.
  - using AI tools can lead to " decline in abilities of cognitive abilities, a diminished capacity for information retention, and an increased reliance on these systems for information" (Zhai et al 2024).
- If traditional coding education involved mastering challenging skills and overcoming high barriers to entry, what new forms of rigor emerge when these barriers are lowered?

Dr. Filipa Calado is an Assistant Professor at the Pratt Institute

School of Information. Her presentation explores how AI technology can be re-purposed not to automate or streamline tasks, but to engage directly with underlying biases that drive these tools. She argues that close attention to the mechanisms of coding and the assumptions that circulate within computational processes can illuminate how bias operates in social and discursive contexts more broadly.

Filipa deploys AI to interrogate its own biases in her research project, which uses Large Language Models (LLMs) to study discourses of transphobia in the US. For this project, she trains an LLM with examples of transphobic text, culled from current "anti-trans" legislative bills that are proliferating across the US, with the purpose of examining the bias and discrimination that result in its output. Each step of data gathering and model development opens the logics and assumptions behind machine learning processes to critical analysis which can lead to surprising realizations. For example, prediction algorithms, which turn semantic meaning in language into numerical probabilities, what Filipa calls a "regularization" or "approximation" of language, reveals unexpected commonalities between polarized political perspectives, surfacing shared investments across transphobic and gender-affirming positions. In this context, AI tools are deliberately deployed not for efficiency or productivity, but as a means of turning them back on themselves, offering new objects and rich opportunities for critical analysis.

outline

- pushing against this idea of "generative AI" toward "critical ML"
  - ML tools offer rich sites of learning and analysis, can be used to resist their own uncritical adoptions.
- prediction according to Wendy Chun
- research on transphobia, studying relationship between approximation/generalization and normalization
  - attachment to normativity that characterizes some trans studies
- live demo of how to fine-tune a model

draft

thank you for having me

toward a critical ML

This presentation explores how AI technology can be re-purposed not to automate or streamline tasks, but to engage directly with underlying biases that drive these tools.

It pushes against this idea of the "generative" AI and more toward critical ML. Using ML tools as analytical methods themselves. They predict not so we can achieve a task faster, but so we can learn more about what has happened in the past.

I am interested in deconstructing prediction algorithms, and how their processes can be a useful heuristic for analyzing the content they are trained on. In this presentation, I use these processes to study social bias and discrimination in text, specifically in anti-trans or transphobic discourse. I am interested in how machine learning processes, whose prediction algorithms can only generate what they have already seen, can bring to the surface some of the ways that transphobia operates in different language contexts.

In what follows, I'm going to "train", or more specifically, "fine-tune" a language model based on articles from the Heritage Foundation, a conservative think tank based in Washington DC. As I am training the model, which should take approximately 8 minutes or so, I am going to explain how the process of training, and what happens to data during the training process, evokes some interesting parallels with debates in Trans Studies scholarship.

prediction, chun

So here is the first intervention I'm making: re-framing ML tools as primarily descriptive rather than generative or productive.

Predictive algorithms are currently used for productive tasks: I've used them personally to generate text like summaries, abstracts, assignment descriptions, prompts. I've also used it to write and debug code, as well as to better understand some code.

I will say that using these tools implicates yourself in a system of vast labor and ecological exploitation. A system that many of us don't ever need to think about, because it's so displaced from our current context in first-world countries (and that is, displaced for now).

We only engage with the final product, because we have the privileged position of being the users at the top of the stack, so to speak, while beneath us, there is a massive operation occuring out of view.

SLIDE kenya article screenshot

For example (here's an example from Kenya), OpenAI paid pennies (literally $2 an hour) to laborers to sift through the most violent pages of the internet in order to clean our datasets;

SLIDE congo drinking water

And beneath them, at the level of sourcing the hardware and computer chips that can run machine learning software, are people whose drinking water has been poisoned by mining operations (here's an example from Congo).

And I'm not even speaking of the energy and water it takes to run these massive models in ever increasing data centers, and the IP being stolen from content creators with no compensation.

Rather, what we do here are people like Sam Altman (the CEO of OpenAI) talk about a world of "abundance" and "infitite potential" – talking as if every step of the AI development process doesn't require extraction or exploitation on a massive scale. But if you are the user, at the top of this food chain of development, you don't see the stack churning beneath you.

So, in light of that, this presentation does not go into how to use ML tools for teaching, as indicated by

START HERE

ML perpetuates relationships

"models not only 'discover' the effects of discrimination; they also automate and perpetuate them for they exploit, rather than remedy, inequalities" (57).

Prediction not as generative or productive, but as descriptive, critical.

> How can we treat machine learning systems and their predictions like those for global climate change. These models offer us the most probable future given past and current actions, not so that we will accept their predictions are inevitable, but rather so we will use them to help change the future. (26)

> What would happen if we treated these and other models as we do climate change models?... not so we will fatalistically accept the future they predict, but rather so that we will do whatever is needed to prevent that future from occurring. (122)

Close reading training data.

> Machine learning and predictive models as they currently exist can also resist reduction, but only if we treat the gaps between their results and our realities as spaces for political action, not errors to be fixed. (254)

vectors, hypothesis, loss (asap)

I'm going to go a bit into technical detail here, because the mechanism of the technology is important to my thinking through my method.

So, to put it most succinctly, the thing that interests me the most about machine learning is the way it works on prediction and plausibility. As many of you may know, all machine learning models (like the one that runs the ChatGPT, for example), make predictions, or guesses, as to what word should follow another word.

But how do they know what an individual word means? Here's the first complicated part: each word, in the model's "understanding," if we can call it that, is represented by a definition, a definition that consists of a long list of numbers. And these numbers, each of them, represent a very, very complex probability for that word's in relation to *every single other word*.

So, a single word is defined by, not what it means in itself, but how it relates to every single other word. (By the way, this is why the models are called "Large Language Models", they are large because these lists of numbers are just massive).

Once a model has a list of numbers to represent each word, it can then use algorithms to calculate which words should be put together, side by side, in a sentence. In this way, text generation is really just turning language meaning, semantic expressivity, into something that can be computed with math, in numerical form.

And here's the second complicated part. To get these long lists of numbers, models must be trained. The training process can be roughly reduced to three steps.

SLIDE - LIST OF FUNCTIONS

1. hypothesis
2. loss
3. minimizing loss

The first step is the "hypothesis" step. Here, a model will take a sample sentence from the dataset, and it will block out the second half of that sentence. Then, it will try to guess which words should go in that second half. Because the model has no idea what the words mean, the guess will be wrong. But that's doesn't matter, because the purpose of the hypothesis is to make any guess, so that it has something from which it build on in the future steps.

Then, after making this guess, it moves to the next step, where the machine checks its prediction against the actual result—it will compare the predicted word against the actual word. And it will calculate the mathematical difference between the prediction and the actual result, which is called the "loss".

Finally, in the third step, it moves to the minimizing this "loss" by *very slightly* adjusting the lists of numbers (attached to each word) so that they are closer to the intended result. The model will do this many times, making incremental changes each time, so progress is very slow, but also very precise. (And this constant iteration of numbers, and the computer processing required to do it, is why language models take lots of time, energy, and computer hardware to train). At each round of training, the numbers attached to each words are slightly adjusted toward the most likely number, which is in effect, an average of that words relationship to every other word in the database.

I read this iterative shifting of numbers (representing words) within the model as a kind of *approximation* or even *normalization* of language. The model generates language by approximating what is most likely, most plausible, based on its training data.

And this is exactly why, while models are good at guessing or predicting, they are not at all good at being creative, at innovating. A model can only generate what it has already seen before. Even a phenomenon like "hallucination," that a model spews text that has no bearing in reality, is based on the tendency of models to repeat what they've already seen. They hallucinate not because they are creative or random, but because they are designed from statistical processes to generate what is most plausible rather than most accurate.

trans affects vs queer studies (asap)

In my project, instead of focusing on what transphobia is afraid of, that is, the fear of gender nonconformity, what could I learn about its positive attachments? For example, what if we turned our attention to the desire for and attachment to normativity?

And this attachment to normativity, in fact, is one way that trans studies has distinguished itself with regard to queer studies, at least according to some scholars.

Trans studies scholar Eliza Steinbock explains that,

SLIDE 16 - TRANS AFFECTS

> "trans analytics have (historically, though not universally) a different set of primary affects than queer theory. Both typically take pain as a reference point, but then their affective interest zags. Queer relishes the joy of subversion. Trans trades in quotidian boredom. Queer has a celebratory tone. Trans speaks in sober detail."

Similarly, Andrea Long Chu has remarked that trans studies, rather than resisting norms, "requires that we understand—as we never have before—what it means to be attached to a norm, by desire, by habit, by survival" ("After Trans Studies" 108).

You'll remember in the list of bill titles from before, the patriarchial undertones in words like "protect," "preserve" and "ensure." Within that language, the fear of change that they imply, there is also some kind of attachment to normativity, to maintaining tradition. It is that attachment that I'm interested in exploring.

Now, in the next section, I'm going to explain why I think that machine learning is a particularly good method for this task of studying normativity.

plausibility (asap)

[SLIDE OF RESULTS]

Here are some of the results that I've gotten so far from my model training. As you can see, the results aren't so great right now. I'm still working on adjusting my model parameters to get more cohesive responses.

But so far, the preliminary results do suggest a certain repetition of language that bears out my point that plausibility that drives text generation. When the model doesn't know what to say, it just repeats what it already knows. Here, I see a fascinating connection between how language models approach language, what they do to language (the normalization or approximation) of language, and what Trans Studies scholars define as an attachment to normativity, that is, a desire to pass.

This makes me wonder, could generated text, as a kind of approximation, a normalization, of its training data, be used to study norms and attatchments to norms in the language that characterizes transphobia? And if so, What might far-right investments in normativity illuminate about trans investments in normativity? What might they suggest about the allure, the "seduction," as trans studies scholar Cassius Adair puts it,of gender transgression?

thank you

SLIDE - THANKS AND CONTACT

Thank you.

And for those of you who want to look at the code and datasets I created for this project, you can find me on Github (software publishing platform) under the username, Gofilipa.