So good afternoon.

My name is Renee Landers and I'm a member of the law faculty and the faculty director for the Master of Science in Law Life Sciences Program, which the course that Robert's going to talk to you about today is a part, it's one of the statistics courses, one of the required courses for the program. But Associate Dean Brigid Sandusky is going to give you a description of the MSLL program after the mini-class.

So in case you're interested in learning more about that opportunity.

So we have been working with Robert over the last two years in helping structure a program for the students in the MSLL program, which as Dean Sandusky will explain to you, and I should call him Professor Smith.

So as Dean Sandusky will explain to you, is designed for people who are interested in going into the life sciences industry.

It's a master of science degree in law. However, people do not have to be lawyers or in a law program in order to enroll in the program. It's designed to be multidisciplinary and a law degree or legal experience is not required, although people who have JDs are enrolled in the program and some of there is an opportunity to pursue a joint program with JD students.

Anyway, I want to say a little bit more about Robert and Professor Smith.

It was really, it's really an honor for me to be here, to be able to introduce him today, because he really is one of the outstanding faculty members of the Sawyer Business School of the University generally. He has, being from New Orleans, he has a degree from LSU. Sorry about that loss the other night and a master's degree from Mississippi State University and his Ph.D. from Florida State University.

His research focuses on the manifestations of consumer psychology, including consumer memory, biases, perceptions and engagement within, within the economy.

And of course, none of those issues are relevant to anything that's in the headlines today.

One of the, he is very well recognized for his teaching on our faculty.

In 2021, he won an innovative teaching award.

In 2017, he won the Student Government Association, outstanding faculty, the Faculty of the Year Award.

He has received a best paper award from the Eastern Academy of Management and the best paper award from the New England Journal of Entrepreneurship.

So his work is recognized both in teaching and his scholarship.

He, in conjunction with receiving the award from the Student Government Association in 2017, the University published a profile of him in the online newsletter, which I commend to all of you, because it really explains in great detail his philosophy of teaching.

And the most, I think the most important feature of his teaching philosophy for our purposes today is that he tries to make
connections between learning statistics and quantitative methods and real world applications of those tools.

And some, a lot of people come to law school or to this program with sort of, you know, insecurities about their quantitative skills.

And I think Professor Smith is one of the faculty members who is able to embrace that uncertainty and move students along to a really good place in learning how to use those skills.

Yesterday afternoon, when I was up at the, the Suffolk I.T. Department,

getting my passwords changed and various other things realigned on these new systems that we have here.

I was chatting with the undergraduate students who were working at the desk yesterday afternoon,

and I mentioned that I was meeting Professor Smith in person for the first time this afternoon,

and both students randomly had taken his courses and had heard and knew fabulous, fabulous things about him.

So it's really an honor that he's teaching in this MSLL program.

And we look forward to his conversation today about one application of statistics in the life sciences.

Awesome. Thank you very much. And I feel like really beefed up after that.

Yeah, I appreciate that introduction.

So it's funny that you give me such a thorough introduction because I was going to start off by making a joke that throughout my time here at Suffolk,

I've been the other Robert Smith. In the law school,

but there's been another professor named Robert Smith has been here a lot longer than me and much more established than I am.

So I've always had this little "S" of shame in my name because he's Robert Smith,

and then it's also my email.

And you know, I had the weird experience last year where I was on an email thread to the whole university announcing that I was retiring.

But it was, yeah, the other Robert Smith was retiring, and I was incredibly excited.

They were talking about the celebration for his retirement.

I was going to be the main person celebrating because I am now officially the Robert Smith at Suffolk University.

And it's a great feeling. So, yeah, as Renee alluded to, I teach primarily the statistics classes.

I am in the business school mostly, but I had the awesome opportunity to teach in the law school, to teach this biostatistics class.

And it's kind of a secret. I don't mention this to my business students so much, but it's actually become my favorite class for reasons that I'll explain.

So today what I'm going to be doing is presenting some work that me and one of my former students collaborated on, and it involves machine learning.

Okay, so I was thinking that I really want to create like a theme for this presentation.
So I was like, you know, I'm talking about my findings from machine learning.

Maybe what I'll do is I'll use ChatGPT to come up with a title for my talk, right?

So I took a summary of my class and the project that I worked on with Brittania and I put it into ChatGPT. I told it, to ChatGPT, that I was creating

I was giving a presentation on this and that was the title it came up with, which I actually don't love because it's a little like snazzy. "Blending the power of" is kind of corny, but I was like "nah, I'll stick with it".

So I created that title. Yeah, Professor Smith, we're not seeing your slides.

Oh, is it not sharing? Okay, let's see.

Sure. Is that working?

Yes, it is. Okay, we're good.

So then I was like, okay, well, now that I've got a title for it, I was like, Well, do you guys know what DALL-E is?

You guys familiar with DALL-E? All right, so OpenAI is the company that owns ChatGPT.

I'm guessing you guys have heard of ChatGPT, and they also have AI that generates images, right?

Using the same textual prompts.

So I was like, Well, now that I've created a title for my presentation, it'd be cool to create a background for the presentation, right?

So I put in some information about my class and I created this background.

It's faded it out so that I could use it.

But this is unfaded, okay? And it's all gibberish, right?

Like the, these codes and signs don't mean anything.

It just took some prompts about artificial intelligence and, and learning and kind of human insights, and it created this.

But it's every bit as good as what you would see on, like, a textbook cover art for like an undergraduate level class.

But the reason why I'm talking about this is to get here.

I actually had to sift through quite a bit of absolutely terrifying images that created, and I'm going to show you guys these images.

But there is a trigger warning here.

They are, they're scary because the actual topic of this project deals with predicting fetal health outcomes.

And the software really fixated on this idea of the fetus.

And then it created some.

Demon spawn babies that,

I don't know why, I think as a parent like these babies, just this is what it felt like taking home one the first time, right?

Oh, I can't even look at that one. This is what it came up with for my backdrop.

And this is the one that I'll pause on because it's my favorite.

I like how that baby looks kind of smug, right?

There's kind of an arrogance to this baby. And it also seems to be like dreaming of some sort of phantom baby, some spirit baby or something.
It's also oddly above the baby. So I decided, I almost used that as the backdrop for the presentation, but I was like, That's too weird. So anyway, yeah, the topic today is machine learning in artificial intelligence, which is permeating every industry in every sector. Right. As I'm sure you're all well aware and I'll talk a little bit about, but to kind of zoom out a bit about my class, well, my class doesn't focus necessarily on machine learning, so it's not quite as structured as this makes it look. But my class, what's pretty awesome about it is that the class sizes are really small, so I'm able to customize the class to the interests of my students. So as students show up, we discuss what they're interested in through a clinical lens, and then we start pulling up some of the major papers, some of the scientific discovery that's happening in those areas. And we started reading them and my students get interested in something and then I go and I find them data on that topic. And then we try to replicate some of these major studies. Right? So this topic is focused on machine learning not because I designed the class to teach machine learning, but because my student wanted to use machine learning to improve health outcomes for pregnant women in emerging economies.

And I thought that was a really cool interest, and I was able to find some cool data, and it just necessitated the use of machine learning as our tool. And so let's talk about machine learning a little bit. Originally, I was going to work through this whole timeline, but I am worried about time because I already talked a lot about demon babies and that slowed me down a bit, but I kind of hit on the major points of the evolution of machine learning. In 1956, there was a conference in Dartmouth where the idea of artificial intelligence really picked up. A few years later, we developed our first supercomputer, the IBM 7090. This was a big breakthrough, and I am going to focus on this because I want to compare where we are now to where we were in 1960. I'll skip a few bullets. Deep Blue. Does anybody know what Deep Blue refers to? Any chess players in here? Deep Blue was the computer program that finally beat the best humans in the world. At the time it was Garry Kasparov was our best chess player and it was in 1997 that computers got better than humans at chess. Now computers are so much better than humans that completely publicly available software, not even software, open access programs that you can get on to your laptop right now could beat Magnus Carlsen, who's the best chess player in the history of the world. So my four year old can open up the computer and he knows the basic rules of chess.
13:42 And he could beat the best chess player in the world using this program that’s available to everybody.
13:46 It's ruined online chess. Self-driving cars.
13:50 You guys are aware of all these things?
13:52 I definitely recommend googling some of the phrases I've put down here if you want to go down a wormhole regarding how artificial intelligence is being used today because some of the applications are absolutely mind blowing.
14:06 So for instance, what Amazon is doing with their Rekognition platform.
14:12 Most of us, when we hear about facial recognition and what Google and Amazon are using it for, we think, Oh, it lets me access my phone or something like that. But actually advertisers are able to use facial recognition, artificial intelligence to get a sense of like the emotions you're experiencing in real time as you use these products, which is pretty awesome or scary depending on how you look at that? My lawyers might be more interested in what JPMorgan is doing, where they are using artificial intelligence to process legal documents and generate legal documents.
14:54 So that's also awesome or scary depending on how you look at it. And plenty of other applications are on this at the bottom, three’s Scout where they use artificial intelligence to scan crop yields at the scale of thousands of miles at a time to identify the crop fields that are distressed.
15:07 Right. The crops, the individual crops are distressed at a rate that obviously humans can't compete with. What I want to focus on, though, is this gap. You'll see like a 33 year gap where there weren't any major breakthroughs.
15:32 And if you ever read a book on artificial intelligence, they will refer to this as the AI Winter, right?
15:39 And it's usually framed as this stretch in time where we just weren't making progress towards this goal of artificial intelligence. And I actually want to dispel that notion a bit because we made a ton of progress in those 30 years.
15:55 Right. So if you know anything about Moore's Law, I don't know if you've ever heard this before, but it's the idea that the number of transistors that we can fit on a microchip doubles every two years.
16:11 Right. So to put that in perspective, because it's exponential growth, to give you an idea of what that means.
16:19 Well, that IBM 7090 that I referenced from 60 years ago, our first supercomputer, it could perform 200,000 operations per second.
16:29 And it kind of sounds like a lot. The computer used a room about this size, the entire computer and it took manual punch cards from human hands to operate.
16:40 I bet it could do 200,000 operations per second.
16:44 Well, the first iPhone could do 400 million operations per second right and it fits in your pocket.
16:51 And we get annoyed when the battery dies. The iPhone Ten can do 600 billion operations per second.
17:00 A modern supercomputer, which is a better comparison to the IBM 7090, can do 30 quadrillion operations per second.
17:10 So in one second, a modern supercomputer can do what it would take IBM 7090, 5000 years to do.
17:18 We made that progress in 60 years. Right.
17:21 That's incredible. And what's really incredible is Moore's Law states in two years it'll double, right?
17:30 That's just mind blowing, right? So that's kind of the scale that we're dealing with.
17:34 And obviously it has applications to clinical settings, right?
17:40 So application number one, which is probably most immediate, is diagnostic discovery.
17:48 So this is Google's LYNA technology which identifies cancer in lymph nodes, and it can beat out a panel of the best doctors in the world.
18:00 Right. So it can identify at a 99% accuracy, and the best doctors in the world combined, the best they've ever done is 96%. So it's pretty incredible.
18:13 We're applying technology similar to this, to identifying Alzheimer's.
18:18 And the, the AI that identifies Alzheimer's performs that are 82%, humans are usually around 70%.
18:29 Again, when I say humans, I mean experts. We are also, you can't see it because of the header, but we're also using this technology to - perfect -
18:44 we're also using this technology to, to diagnose diabetic retinopathy,
18:51 which I don't know if you guys have any loved ones or know anybody that has diabetes,
18:56 but one of the side effects of diabetes is blindness because of hemorrhaging in the blood vessels in the retina.
19:05 And this is then something that doctors have long struggled with,
19:11 but that computers have been able to tackle by processing at a very large scale these images and images such as this
19:22 that I'm talking about, thousands and thousands of these images.
19:26 And so I don't want this to turn into an artificial intelligence talk because I can talk about this topic forever.
19:32 Right. But some of what we're doing with artificial intelligence is pretty incredible and also pretty scary.
19:40 Another application in a clinical setting is personalizing treatment.
19:45 Right.
19:45 So without getting derailed on this too much, doctors obviously, alright, I'm going to state an opinion, have a lot of biases when they assign the treatment.
19:56 Right. And while the artificial intelligence could also be biased,
20:03 removing human bias in industry, so there's different treatments that can be used to tackle the same condition.
20:12 And obviously this is removing some of that human bias.
20:17 And then finally, drug discovery.
20:19 We're actually discovering new antibiotics simply by dumping a ton of compounds into AI models and letting the AI discover new treatments,
20:31 which is pretty incredible. All right.
20:34 So my student and then intern, my student and I became interested in applying this idea to predicting perinatal health outcomes.
20:45 Right. So I want to take a second and talk about why this is important.
20:51 So this topic is important,
20:54 I think it's obvious to some extent why it's important, but I want
21:04 right, and you think about how life expectancy has changed, for some
21:14 Okay, so if you were to plot this on a timeline, it actually
21:20 because for the first half of this graph we're covering 12,000
21:28 Right. I don't have enough room to actually show the evolution of
21:34 All of our progress has happened in the last hundred years.
21:38 Like if you look at that, we give you guys more precise numbers.
21:43 For 2000 years of human existence or for 12,000 years of human
21:55 And in the last 120 years, we've increased it by like 140%.
22:00 Right. So it's an incredibly, it's obviously due to improvements in
22:08 Right. But the problem is access to that isn’t equivalent across the
22:15 So if you look at how child mortality has changed,
22:20 see experts attribute much of this gain in this graph to two
22:30 And if you look at how child mortality has evolved in the last 200
22:43 And you can see obviously across the world we're seeing improvements
22:52 And so that was a selection of eight different nations.
22:56 But here is everybody this everybody had data on.
23:00 So I created this visualization. Our Y-axis is child mortality
23:06 Right. Our X-axis is income, so how wealthy the nation is.
23:11 The size of the bubble is the size of the population of that nation.
23:16 And then you can see the year. Right. And we're going to watch it
23:20 Now, I sped this up really fast because I was worried about time.
23:23 The visualization when I originally created it takes about 30
23:27 So you have to watch fast and. So you watch the bubbles grow.
23:33 Watch the population growing larger as our nations become more
23:39 you'll see here is I'm zooming in on the y axis that you can see the
23:46 and you can see our African countries are in blue, that it's not,
23:56 these, these emerging economies are where the United States was in
24:01 Right. And the thing about machine learning and artificial
intelligence is it's so much more scalable than humans are.
Right. In these emerging economies, they don't have access to the same doctors that we have access to here. By creating machine learning algorithms, we are thereby removing the need for as many of those health care professionals. So this is why the topic is important.

Also looking at maternal mortality you'll see the exact same effect, I'll slow down the video and around the sixties because I didn't have data before the sixties.

So I really sped it up. And you see this in video that same relationship as with child mortality.

All right. So let me talk about our data. Let me talk about what we actually did with this.

So we use CTG data. And if you don't know what CTG data is, it's how we monitor a fetus's heart rate during the pregnancy. We were looking at the third trimester, the final trimester, and we had 21, we had access to a dataset of over 2100 fetuses.

Right. So we were looking at things like what's the baseline, fetal heart rate, how many acceleration were there, how many deceleration, were there uterine contractions, did the heart rate zero and how often did zero out and peak, etc., etc.

A lot of features focusing on the volatility of the heart rate.

All right. So I'm going to have to explain very, very, very quickly what machine learning actually is and what binary classification is.

Now, I want you to know that I'm going to blend in maybe three different topics that I would normally spend like a month on. Right. So this is going to be a speed run on machine learning and binary classification.

All right. So first, I'm guessing you guys, I know my students do, but what about the law students?

You've heard of it. Yeah. All right. Real fast recap on linear regression.

With linear regression, we're predicting a continuous outcome. In other words, we're predicting an amount of something, right?

So in this case, if we wanted to predict someone's blood pressure using their age, we might use linear regression.

Now, the simplest form of linear regression is conveniently called simple linear regression.

And it's where we have one independent variable, one x variable on the x axis gauge, predicting one dependent variable.

We would plot this relationship using a scatterplot. This should sound pretty familiar to most of you. We would create a model.

The model we're going to visually represent is a line of best fit. It is a line that minimizes the difference between every real observation in the predicted observation, right.

What's awesome about linear regression in the simple form is we can calculate the best line.

There is no, it's not an approximation, it is the best line.

You guys have probably seen this formula before. Y is what we're predicting, blood pressure, beta zero is our intercept, right,
it's where our model intercepts, so it's basically, it's the model's prediction when your x variable is zero, right?

So when you're zero years old, this is the prediction for Y.

And then we don't really need that for today or we do need to understand sort of is what a beta coefficient is.

A beta coefficient is what the model's predicting will change in y - blood pressure - when we increase x - age - by one.

Right. So as I increase age, how much does my blood pressure change. As I was making these slides, I realized why I'm using a hypothetical data set?

I have real data on this as I took my real data and I created this simple linear regression, right?

So this is literally what a model would predict.

Now, again, this is a very simple model, so it's not going to be very accurate.

But here's real data looking at the relationship between age and systolic blood pressure, and what we're seeing here, our data is conveniently, basically one, so that every year we age, our blood pressure is predicted to go up by one.

Our intercepts 82. So this model's predicting a zero year old to have a blood pressure of 82, which is actually very inaccurate based on my Google searching, maybe the blood pressure like 40-something currently.

All right. But a simple linear regression model is not going to be very accurate because it's only got one feature.

It's only got one variable it's using to predict off of - age.

Okay, enter logistic regression.

Now, I would normally spend about a month teaching logistic regression, right, if I wanted to teach this to you properly.

Logistic regression is based on the same mathematical principles as linear regression, but it's more complicated.

With logistic regression, we're predicting a categorical outcome.

Right. And believe it or not, that's a more common need is to predict a categorical outcome.

So to think about meteorology, a meteorologist would use linear regression to predict how much precipitation we're going to get tomorrow, but they would use logistic regression to predict will it rain?

Right. And a lot of times that's what we care about, is will something happen, yes or no?

And that's when we need logistic regression.

So the problem with logistic regression is we want to model this linearly like we do with linear regression, but look at our data.

It's all weird because you only have either heart disease or you don't have heart disease, right?

It's yes or no with logistic, it's binary in this case.

Right? So because of that, we have to perform a logistic function on our model. It creates this little S-curve and this is hypothetical data, so don't freak out,

but basically what this is saying is at a young age, this is your probability of heart disease, by the way,

so at a young age, as you get older, there's almost no impact on your probability of heart disease.

And then what you get to about my age, that changes pretty rapidly and then it slows down. Again,
this is made up data. And as I was putting this together, I realize, again, I have data this, let me just use the real data.

Problem is you don't see the full S curve. The traditional logistic regression model function has an S curve to it.

Well, but that's good news because, based on the data that I have access to, your probability of heart disease never clears 50%.

So it's good. The bad news is, is because something else kills you, kind of a dark direction.

Okay, last thing. Our output in logistic regression is in terms of odds ratios.

Okay. So what an odds ratio is, is it's the probability of something happening relative to the probability of it not happening.

Right. Kind of simple. So if there's a 75% chance that you become MSL students, the odds ratio would be three, right?

Three times as likely to become a student is not, right?

So it would be your odds ratio if there was a 90% chance, your odds ratio would be nine.

Now, the reason why this matters is that we can't model things in terms of probabilities, because probabilities cap at 100%.

So if you remember what a beta coefficient is, it's showing. well, every time we increase x, what's happening to y?

Well, if we did this with a probability, alright, let's say our beta is five.

So every time you get a year older, your probability of heart disease goes up by 5%.

They won't take long before your probability was over 100%.

That'd be very bad. So that's why we have to use odds ratios, because odds ratios go up to infinity.

There is no artificial cap on them. If you think about what an odds ratio is for long enough, you'll realize, Oh yeah, they can go up forever, right?

As a probability, asymptotically gets closer to one and odds ratio just rises to infinity.

All right. That's the background that you need to know to kind of understand what our output is.

I'm going to skip these slides because I'm a little worried that I'm talking too long.

My student and I performed exploratory data analysis, as you would do before running any major model like this.

So the first slide, actually, I will pause.

This is our dependent variable. This is what we're predicting.

There's three categories. We've got a normal fetus, a suspect fetus, (this is not my coding) and a pathological fetus. The way we have those classes

Those classifications is based on a team of obstetricians.

I think that's right. A team of obstetricians look at the data and they assign them into those three categories, all 2200 fetuses.

Right. And what we're doing is we're going to take those classifications and we're going to build a model that can replicate that.

That we're going to use it to teach the model how to identify a fetus as either normal, suspect or pathological.

And then we're going to test its ability to be as good as those doctors were going forward.
It's really powerful stuff. So the first thing we did is look at those classifications. You can see 78% of the fetuses were normal, 8% were pathological. I'm going to skip these. We did a box plot to get rid of our outliers. We did Nested Histograms to just kind of look in on every variable and its distribution, get rid of any messy data. We did this correlation heatmap where we can look at some of the really hot relationships and you want to remove those redundancies from your model. If you guys have questions about that, I can elaborate after this presentation. This is what I want to pause at because this is what we're doing with machine learning. We're taking all this data and we're going to separate the data into two groups. 70% of it is what we call training data. Okay, so this is where we take the machine learning algorithm and we give it the answers, right? We give it all the CTG data and we say this was a pathological virus. And then here this is a this is a normal fetus. And we do that for 70% of it. And it creates an algorithm itself. It creates beta weights itself and optimizes these data once it learns. Right, this is what is called supervised learning. The model gets smarter and smarter because it has the answers and eventually it gets to where it's got basically, basically perfect accuracy, at least in our case. But then we take that other 30% of the data. We left that out, right? And then once we've built the model, what really matters is how it performs on the test data. That's our approximation of how this model is going to perform without us there in an unsupervised way. How is this model? Can it replicate what that panel of expert obstetricians could do, right, without us there. And if it can, then that means it's, it's got utility. It's something that we can offer to, to these settings that they need more resources in their health care practices. Right. So this is what Brittania and I were dedicated to doing for the semester. Here's our syntax. If you don't like programing, this will scare you. But I shield the students from it that don't want to get messy with it. So you don't have to do this. This is 200 lines of code that I wrote, but the program is much more sophisticated than this will even look because for those that don't know anything about coding, the first 20 lines are actually importing entire libraries and modules of other programs. So it's obviously, like we're doing machine learning, the program is pretty sophisticated.
All right. So our findings, we're going to gloss over the beta coefficients, mostly due to time. But to kind of remind you or maybe to point out the complexity of logistic regression, these coefficients are not intuitively interpretable because they're in units of log odds and I'm not even going to take the time to log odd is, but these odds ratios are a bit more interpretable, right? So what this odds ratio is saying is that when we increase this independent variable by one, this is how much the odds of being a one, in this case, a pathological fetus goes up, the odds, remember the odds, not the probability. Right. So what you could do is subtract one from this odds ratio and think of it as a percentage of change.

So when you increase a normal short term variability of the heart rate by a one, the odds that this is a pathological fetus goes up by 550%, it's a very big impact. So I'll skip right over to our takeaway slide. This is how good the me and Britannia's model was. The model was 97% accurate. The best way to think about this is this model is 97% as good as a team of doctors. Me and the student put this together in one semester. So that's the predictive power, the precision here is how accurate the model is when it identified the pathological fetus.

Right. So the precision was 95%. That means if it said that we have a pathological fetus here, 95.3% of the time it was right. Precision is a, is a, oh yeah that’s why I just said. Sensitivity is a little more difficult, though, because if you look at this, most fetuses are healthy, right? Most of these fetuses were correct. What's hard is to find the needle in the haystack. Right. So the model was right, 70.7% of the time at identifying those needles in the haystack, which is actually pretty good. The specificity in this case, that's the model's ability to find a negative case.

So when it said when we had a healthy baby, I shouldn’t say baby, when we had a healthy fetus, how accurate was it at identifying is healthy, it was was 99.7% accurate. So that's pretty powerful stuff, especially for a student with almost no statistical background to pull off in one semester.

The model approximated expert human performance, not regular human performance, but a team of expert obstetricians. And most importantly, you know, CTG is that the ability to perform ongoing monitoring of CTG data is not accessible to all continents, right? To be able to monitor, to replicate this with machine learning technologies would be pretty impactful for those situations.
So that's everything. I have no idea how I did on time. I'm sorry if I'm way over.

Okay. I think we're all right. I'm sorry if I was talking fast there are guys who started to realize I packed a lot in this presentation.

Thank you so much Professor Smith. I am sure both in Zoom land in here in the classroom today we'll have some questions for you. But first, we're going to kind of continue with our presentation.

My name is Bridgett Sandusky. I am the Assistant Dean of Graduate Law Programs here.

And the Master of Science in Law: Life Sciences program is one of several degree programs that I oversee here at Suffolk.

Okay. So I'm going to - bear with me for a moment - as I start to share.

So I know some of you are Suffolk students either at Suffolk University or at the law school, but I also know that we have some visitors online and some visitors here in the classroom that aren't familiar with Suffolk and who we are.

So I thought it'd be helpful just to tell you a little bit about Suffolk and our vision of what it is that we do.

And I think Professor Smith here today really demonstrates Suffolk's vision accurately for you, of faculty members who are able to take really complicated and complex information and make that so much more readily accessible.

We are grounded in a practical education from our founding. In 1906, we started as a law school and then grew as a university, but we always focused on providing our students experiential opportunities and that is becoming ever more important.

And that's why many of the classes that you will find within the Masters of Science in Law: Life Sciences program are going to have that same grounding, that grounding and providing information, so you're going to learn within the classroom, but many of the classes are going to have a project based, similar to Professor Smith today, but he is certainly not alone, in which students are taking that information and developing projects.

So information that's going to be helpful and useful for you when you're taking this degree and going out into the real world with it.

And so we do that both with this brand new degree, which I'm really excited to talk with you about, but also within our JD program and at the University.

So the Master of Law: Life Sciences, it is, we launched it during COVID, probably not the best time to be launching a degree program, but it was an opportunity.

We have been developing it for a number of years. So first and foremost, we did a lot of research.

We went out into the market to talk with individuals.

We went and talked to the scientists and said, What is it, when you talking with an attorney in the biotech pharma sector, what is it you want them to know?
And we went and we talked with the attorneys and the same thing. So what this degree is supposed to be doing for you is filling in those gaps. So you don't need to be a scientist to come into this program. You don't need to be a lawyer to come into this program. We are going to fill in whatever educational gaps that you might have. So you will have a firm grounding in both science, business and law. So it's really unique. We believe that it's still one of the only programs structured specifically like this in the United States, potentially in the world as well. There are some other programs that might be geared to specific subsets. So just for people who are scientists, for example.

But our program is really wonderful in that it allows individuals from all different types of backgrounds. So if you're in a class like Professor Smith's class, you're going to have students that are attorneys, students that are coming from a business development background, students that are scientists that are looking to learn more about business and law.

And it really is reflective, this degree is really reflective of what jobs are today. We're no longer, jobs are not just siloed. Right. We know that in our jobs were expected to wear so many hats nowadays. So shouldn't we be engaging in education that's going to be reflective of that? And so this and offering an interdisciplinary degree in which you have faculty members from Suffolk Law School, from Suffolk, from Sawyer Business School and from our College of Arts and Sciences, really reflects that.

And we're really excited about it. And of course, the life sciences in the state of Massachusetts is really the main reason why we developed this program was because there has continued, long before COVID, there has been a continuous growth within this sector.

And we were hearing and you can read in the Boston Globe, for example, there is always such a need for people in Master's and higher level positions within biotech pharma companies, and they're actively recruiting and stealing talent away from the various different companies because there weren't enough people.

So Mass BioEd every year puts out the Life Sciences Workforce Trends report. And so that's where we're grabbing this data from. A 67% increase in life sciences jobs over the past decade.

They're projecting 20,000 new biotech pharma jobs by 2024, and it's highly concentrated. And this next slide really reflects that quite well. You can see from 2017 to 2019, Massachusetts life sciences jobs grew by 17%.
Blowing away what it grew over the rest of the United States at 4%, which is really great, still terrific. But. So much more needed outcomes. It was Lifesciences 9% for those, but more than double, almost double the growth in Massachusetts for life sciences positions versus life sciences across the United States. And then in reference to 2019 and 2020, still Massachusetts continued to grow a reasonable 3% when we saw growth across the United States and in Massachusetts, other private sector jobs retracting quite substantially. So it is a stable but also continuing to grow. And we expect that to not be stopping any time in the foreseeable future. Over this five year time period, we saw 55% increase in job demand during that time period. 10% alone from 2019 to 2020. And there's a projected 9.2% by 2027. So that means what? Jobs. And we think our program is able to prepare you to enter into a variety of different roles. Obviously, employment outcomes are going to be dependent upon what it is you're coming into the program with already. So if you're not already an attorney, we're not going to make you an attorney in this program. And if you're not already a scientist, we're not going to make you into a scientist, but we are going to teach you the terminology. We're going to teach you the language so that you can enter into a variety of different roles. So the structure of the program, the program itself is comprised of 30 credits, and that will include ten required courses. Those courses are three credits each. Now you'll see in the next slide that the different courses, biostatistics with Professor Smith, is one of those ten courses. You can pursue it in on a full time basis or on a part time basis. There's a great deal of flexibility built into this program's structure. Part time: you can go really as fast or slow as you want. A year and a half to over two and a half years. And then we're completely test optional. So no, GRE, GMAT, LSAT is required. And for any international students that might be joining us here today, this is a STEM approved degree. And so that is really great news for students that are F-1 visa holders because it allows them to stay for the 12 months of OPT and then renew for an additional 24 months. So three years in total. So they complete the year the degree in one year and then they're able to stay work in an organization, company, government as long it is, as it is related to the degree itself for the next three years. So that is a huge benefit for any of our international students. And you can start full time and you can start in the fall semester. So that would be an August start date. Part time students, you have the option to start either in August or in January.
There's two start dates for that. Our priority application deadline is in May 15th for the fall, so there's still plenty of time to be submitting applications for fall of 2023, and most of our classes will be held at 4:30 p.m. or later. So that's convenient both for our full time students that might end up securing internships within the life sciences field, and that is something that we help and we assist with.

So particularly if you do not already have any sort of background working within biotech or pharma, that is something that we would be working with you to help you pursue an internship and experiential experience during your time in your program.

And then for part time students, that means you're working during the day and then you're coming to class at night. And the nice thing about these courses are they're in blocks. So it's potentially you might only be, you could as a part time student be in class once a week.

You could have class from 4:30 to 7:10 and then 7:15 to 9:50. So if you think about that as a person approaching this as a part time student, you know could I do graduate a graduate program one night a week?

Yeah, I could do that. I think most of us could say we could do that.

It's not something that you need to be here four days a week and in doing that.

So I think there is that flexibility for students.

Every single application that is submitted will be automatically reviewed for merit based scholarship potential.

So you don't need to be submitting any separate documentation, for example.

And the vast majority of the admitted students will receive some level of merit based funding, ranging up to about one third of total degree cost.

Here are our current ten courses.

It's really structured as half the program is more geared toward law courses, and half the courses are geared more towards science courses.

This introduction to molecular biology for professionals is really our foundational science course.

And so that's going to be unlocking your other more sophisticated science courses,

so applied genetics therapies, clinical research, etc., and then you are going to have them intermixed.

So if you're a full time student, five courses in one semester, five courses in the next semester; part time students, it could be as little as two courses in a semester, upwards of four courses, if that's the intensity that you wish to pursue.

I think it is worth sharing, although I know Professor Smith, makes tonight's data really approachable and this is so interesting, I also know sometimes that might be – you’ve got to take note, he said “I would be teaching this for a month. I'd be teaching this for two months.”

So if things were really kind of going over your head, keeping that into perspective that he was trying to give us, kind of focusing on outcomes,
because we know it's impossible to be teaching a biostatistics course in 30 minutes. You can't do that. So we decided it would be best for him to really focusing on what a student actually did within the class, within the classroom. But we are not making you into statisticians, unless you already are. As I said, we're not making you into an attorney if you aren't already one. What our job is to do is to make sure that you understand the language and the terminology. And so if you're already an IP attorney and you have applied to this program, you're not going to take the Intellectual Property Survey course. So we custom designed the program to your own individual needs and educational background. So if you already have a STEM degree and you said I took statistics, you're not going to have to take it again. We will evaluate that, we’ll ask for you to secure the syllabus for the course that you took. And then we send it to the experts. So I'll send it to Professor Smith and he'll say, Yeah, they cover 90% of what I would be covering. There's no need for them to replicate that and take this course. And then we find a course that's going to add better value to your degree. So maybe that's a health law course, maybe it's a FDA food and drug policy course, and maybe it's another business related course if you're interested in that. That is really what makes this program so, that we're able to gear it and structure it to a wide variety of individuals. And so if you have a degree in molecular biology, you're not taking the intro to molecular biology. And that's the flip, too, because often students that are coming from a legal background will say there's going to be people that are molecular biologist in the classroom. No, we're not having them in that classroom with you. It's going to be a subset of students that should be in that classroom that haven't taken that course. So it's really important to focus on that, that the courses themselves are geared toward the particular student type within that course. And they're small enough so that these courses, particularly with the science based courses, are intentionally small. So a faculty member is going to know if no one's getting it, they're going to be able to see it and they're going to be able to, you know, reevaluate. Okay, let's go back, review this and make sure kind of everybody's on board moving ahead. So if we're talking about ten students, it's much easier to be able to do that. We're not talking about 100 students in a science course, and none of the science courses do not have labs. So they are just purely course based courses -
there are no labs attached to those particular courses.
Here's a listing of potential employment outcomes.
These are going to be, as I said, really variable dependent upon your prior educational background, your prior professional experience potentially.
So as I said, we're not going to make if you aren't already an attorney,
you're not going to have an employment outcome of a biotech transactions attorney, for example.
And, but there there's going to be a wide variety of different types of employment outcomes that we can also discuss with you on a one on one basis,
taking into consideration. And I am here as part of a team.
And so you met today earlier, Professor Landers, who is the academic director.
She also teaches the data privacy course. And then online tonight and on Zoom,
we also have director Jennifer Karnakis, and.
she is the executive director for the Intellectual Property Center here at Suffolk, and she was a life sciences attorney for a number of years,
so has, in Massachusetts, in Boston, so has a really wonderful an amazing, strong and deep network.
And because this program is interdisciplinary,
we're able to draw upon both the resources of the university's career center, as well as the law school's career center.
So those, the MSLL students are really lucky in that they're able to, because of the interdisciplinary aspect of this degree,
able to draw upon both the strengths and the alumni base that we have across the entire university.
And I think it also bears saying that many of the faculty members that are teaching,
whether or not they're full time faculty members or if we are drawing on a couple of individuals teaching within the program are adjuncts,
so they're a compliance, they have a compliance consultancy firm that they're doing every day,
and then they're coming and they're teaching compliance in the life sciences industry.
And so really bringing in individuals that are teaching with a lot of real life, hands on knowledge.
So this isn't just what it says in the book. You know,
let me tell you about what happened today and really bring in prior work experience that they've had prior to coming and teaching within the program.
Here are several upcoming events. So Director Karnakis will be holding several virtual meet and greets and next month, they are held monthly.
And then we have a graduate open house later this month, on March 25th, from 10 a.m. to 1 p.m. Eastern Standard Time.
I would encourage you to come and visit us at one of those times as well.
And so this is my contact information as well as for Professor Landers and Director Karnakis and I would be happy to open this up,
I know we're a little bit past our 6:00 time frame, but if you have any questions for me about the program or some questions for Professor Smith as well, those that are online, I can see, I can go back and I see that there's at least one chat question over here. So if anybody here has questions, feel free to questions. So one of the things I really like when you were talking about how hard it is to see something going on, was I just kind of like defining [unintelligible]? Yes. So that. Oh, yeah, that's a great question. So what I'm referencing there is a mathematical computational method. So the way that you heard “neural network”?

Have you heard of it in the context of computer science or artificial intelligence? It's the same thing. It's like what you learn about, right? So each connection in the human brain is literally just electronic signals from one neuron to another. Well, in a neural network of a computer, it’s the same thing. And there is a mathematical operation that’s going determine whether or not the signal is sent. That's right. So that they can perform 30 quadrillion mathematical operations a second, determining whether that's sent. Yeah, that's a great question. Just trying to know that.

Yeah, I'm sorry, but a bigger question, I guess, we were talking very briefly at the beginning of your talk, I was just wondering when you were constructing your model, I guess I try to avoid some of those biases too. So I didn't know that was an issue.

There's a common misconception that there's not bias involved in data science, and that’s just not true. There’s going to be bias and the complexity of data science is trying to remove all that bias. That’s why statistics class is so complicated, we are trying to remove the bias. So what's actually interesting right now, in artificial intelligence, is that these neural networks are so sophisticated, so complicated that humans are struggling to even figure it out because the output, without getting, making this is a whole lecture on artificial intelligence, the output data that you get, we’re not even like, well, ChapGPT generates some text for you, the model that creates that text is so complicated that the humans that created that model don't even know why that data got generated. Right.

So it's becoming more difficult for humans, if that makes sense. There’s a question about OPT extending to 18 months, you can extend to 18 months. That is not a problem. You have to be at least a minimum of nine credits or more to be a full time student on an F1 student visa. So if you wanted to be completing it over a period of nine months, you would have the flexibility to do that. But there would be very sort of specific courses that we would have you be doing just to make sure that lock step you're taking the right sequence.
Simple question, so most people on the program, are they full time or part time? It's a mix. It really is. I think we do, it’s still a what we would say a small program, or it’s still in the building blocks of even doing that, but there is there's a good mix of both and part time. We also offer this as a dual degree for our J.D. student population as well. And so we do have some J.D. students that are that are in the program. Generally speaking, they have been full time as well. Other questions? Okay. We'll make sure online. No, I think we are good. Well, thank you so much, everyone, for coming and attending tonight's mini class on biostatistics. I hope many of you will consider in learning more about the Masters of Science: Law Life Sciences at Suffolk University Law School. Thank you.