Participant #5: Yeah, okay cool. So this was, I'm trying to remember how this thing works right? I read a text description and then there's this thing with the... this was movable at one point right? Oh it still is, okay. Let's stop right here. Sure, so how did I pick this?

Interviewer #1: If it helps, you can click the show description button, and it should bring out the description.

Participant #5: Ah, this will bring out part one? [crosstalk] Or the summary of that part?

Interviewer #1: Yeah.

Participant #5: Yeah, this was the important part. Okay, so what I remember. A lot of what I picked here was sort of remembering... trying to remember the numbers.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: I remember I sort of did part one and part two not quite at the same time, I sort of had a conversation in between, so the numbers were a little out of my head. But I remember it was like 25 and 50-ish for the two conditions... 25 and 45 it looks like is the actual numbers that you saw in practice. So in terms of the intercept, basically tried to match it, which I think I kind of got right in the neighborhood.

Participant #5: As far as why a student as opposed to a normal rule of thumb seems intercepts are relatively well informed in a lot of things right? And plus on model it's just kind of the average base rate, so you'll have a lot of information, so you can get away with maybe a slightly looser prior.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: Wait no, I picked the normal. Is that what this is?

Interviewer #1: You picked the normal... yes, normal entry one.

Participant #5: Now I'm just ex post rationalizing aren't I? I picked this? Really?

Interviewer #1: I think so.

Participant #5: Oh I did a bad job then. I like the other one even more.

Interviewer #1: Could you elaborate on why you think you did a bad job?

Participant #5: Well, it looks really... oh, okay yes, this I actually remember being confused by, right? This is a Poisson model right?

Interviewer #1: Yes.

Participant #5: A Poisson regression? So I remember actually being confused about this at the time. The intercept is like the log of the mean number of observation.

Interviewer #1: Yes.

Participant #5: Right? Like if that's supposed to be 25-ish in the base case, or even call it like 34, based on this text right here. Log of 34 is like seven, give or take.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: Not a lot, so I wanted to push this as far to the left as possible.

Interviewer #1: I see, so I think one thing I made a mistake here is... and I don't think it was a mistake in this survey but I can pull it up and show you... like multiple prototypes which is...

Participant #5: Yeah, right like if the mean is like 36, I would want a prior center around like 4-ish.

Interviewer #1: Okay, so.

Participant #5: That's why I pushed it as far that way as I could.

Interviewer #1: Yeah, I think what you saw in the survey... it's the prior probability identity of the intercept on the... Ah I see, it-

Participant #5: Like these numbers should be on the response scale, not the coefficient. You know in the hundred-ish range right?

Interviewer #1: Yes.

Participant #5: So I remember this label turning me around for a bit... like, visualized here, 3-ish is about the right number, so a normal centered at 3 is what I wanted.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: Like this, I was okay with. These labels got me in the wrong place.

Interviewer #1: I see, okay. So if I told you this was the density on the response scale, what would you have chosen?

Participant #5: Yes right, so if this had been like expected response...

Participant #5: Actually, I thought this wasn't bad.

Interviewer #1: Mm-hmm (affirmative) interesting.

Participant #5: This is centered at 25-ish. An eyeball, maybe you would, wait, I think it's to the left. But yeah, I mean, everything on here is not bad.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: This is maybe a little heavy, I don't know. The y axis might be helpful. So that's not bad if you are trying to center it at 25, right? If this is the response.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: In general, this is basically just the mean of the base case, so I don't think I would worry too much about it, just because I know that is going to be pretty well informed by the data.

Interviewer #1: Mm-hmm (affirmative). So, when you are deciding on what seems reasonable, what are the factors that you consider?

Participant #5: Matching the mean is a big one, right? Here being that 25, 30-ish number. Being not too crazy high, like, that... That's not what is happening here, actually. Right, so, my two [inaudible] are location and scale, okay, I can't screw with the degrees of freedom?

Interviewer #1: No, yeah, we fixed it at three, I think this was in the first page, but, yeah I missed...

Participant #5: Yeah, it probably was. Yeah, so, I would not want, for instance, a heavier tail than this [t(3.5, 0.6)]. I wouldn't want more than this 150 range. In terms of matching the second moment, the scale parameter, anything around here [t(3.5, 1)] looks reasonable enough. That end (the right tail) probably looks a little heavy to me, just because there is daylight under 100. But anything, once you hit here-ish looks reasonable. That [t(3.5, 0.2)] looks maybe, a little strong. This is a totally arbitrary thing, but a 0.2 seems like a small prior standard deviation. Just a gut feeling.

Interviewer #1: I see.

Participant #5: Yeah, psychologically, intercept, you get a lot of information about, at least in a simple enough regression like this, so I wouldn't mind having a little bit more standard deviation, a little more ambiguity, because I think it is going to be okay at the end of the day.

Interviewer #1: Mm-hmm (affirmative), I see.

Participant #5: Yeah, yeah. So, match the mean, maybe a little more standard deviation than you think you need, but, my big fear in general would be heavy tails plus Poisson leads to crazy numbers.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: That is what I would be worried about.

Interviewer #1: I see, yeah. And, when you say you matched a mean, what do you do, how do you match, and go about doing that?

Participant #5: So here, it's... I sort of know it is about 3.5, just based on the text you said. I un-log it, I un-transform it, I take the log in my head and know it is going to be around there. I didn't do this at the time, but 35, 3.5, it feels about right.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: And then, yeah, in a world where this said "average response" [crosstalk] does immediately intercept, then I match the hump. I understand this isn't the real mean, right, because it is asymmetric, but good enough for government work.

Interviewer #1: Cool.

Participant #5: Yeah, so really, here it's just kind of, order of magnituding it in my head. Here it is hump matching, versus where it actually should be.

Interviewer #1: I see.

Participant #5: Based on the text.

Interviewer #1: Mm-hmm (affirmative). There seems to be a problem with this one. I am sending you another link, if you can open that up.

Participant #5: This link?

Interviewer #1: Yes. If you scroll down, you can ignore the first one, you've already seen that.

Participant #5: This one, yeah, okay.

Interviewer #1: Yes. Do you remember seeing this one?

Participant #5: Yes.

Interviewer #1: Okay. So again, the same questions. How did you decide on the prior, and the prior that you chose is zero centered around zero and, the scale was 0.8, and you chose a certain scale distribution.

Participant #5: That was kind of...

Interviewer #1: Yeah, something like that.

Participant #5: Yeah, like, this-ish?

Interviewer #1: Yeah.

Participant #5: Yeah. So, why did I pick this. This, and this is kind of a little bit what I do in consulting work, and I think it's right for any study. For any sort of scientific study where we are trying to say "this effect exists," you want a prior around the fact that it does not.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: This is centered at, there is no effect size. An odds ratio of one.

Interviewer #1: Yes.

Participant #5: Right, and that is just in theory, like, the burden of proof needs to be on the experiment. If I went in and said, that, and then there is an effect in my data, then somebody should be skeptical and say, is there really anything there?

Participant #5: I do this when I am working with a collaboration and whatnot, I tend to, for the things that they want to see, I tend to be a little more adversarial. Even if they think there is something there, I don't want to put that in. I want to let the experiment, the study to show that it is really there.

Interviewer #1: I see, yeah.

Participant #5: Just because of how academic publications work. That sort of consistent was the more standard testing type of approach that they are used to, and their communities almost certainly expect. So, it clearly had to be centered at the effect size of one.

Participant #5: In terms of the size, how that versus that, a little bit wider, because that is going to allow for reasonable affects, right? If I remember from the text description, the effect was actually not insignificant.

Interviewer #1: What do you mean?

Participant #5: I am trying to remember. What was expansive condition, that's not right.

Participant #5: In the text, I was trying to remember what this variable right here condition actually meant.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: It says, "restrictive versus expansive condition," but I don't remember what those terms really mean.

Interviewer #1: Oh, I think [crosstalk]

Participant #5: Sorry, go ahead?

Interviewer #1: Oh no, I mean, if you just want me to give you a brief reminder of what that was?

Participant #5: Yeah, if you don't mind, I am trying to reconfigure my thought process.

Interviewer #1: So, the experiment set up was like, participant, and the control condition had their hands very close together, they were, almost in a constrained posture. In the test condition, their arms are wider apart, so they were sitting in a more expansive posture. So that was...

Participant #5: Ah, okay! So it was how the human was arranged.

Interviewer #1: Right, and they had to pump up balloons sitting in that posture, so that was what they were trying to do.

Participant #5: I don't remember that actually playing a huge role in my thinking. I think in general it was more like, this should be relatively wide because we, in virtue of doing the experiment, we do expect something to happen here.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: Right? I think if you genuinely believed in this kind of a prior, oh, actually. In general, if you took an even more extreme version of that, that might suggest you don't actually think there is an effect, which deems inconsistent with doing the experiment in the first place.

Interviewer #1: Mm-hmm (affirmative), I see.

Participant #5: But you know, looking a little more closely now, a half to two times is not actually small effect. This might be more reasonable that I first thought it was.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: But yeah, just in general, allowing for some effect. Yes. Looking at it now, it is too wide.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: Right? I feel like I heard a rule somewhere once that, and this was for medical data, so it's not exactly the same but, smoking only has an effect size of five on a log scale, on getting lung cancer. That is one of the strongest effects we know in the entirety of the medical literature.

Interviewer #1: Mm-hmm (affirmative), I see.

Participant #5: So the fact that this is pretty okay with being anywhere from a five to a tenth.

Interviewer #1: So by...

Participant #5: Feels wide.

Interviewer #1: In smoking, you are saying the effect is five times? Increases the chances of lung cancer by five times?

Participant #5: Yeah. I mean, it is an odds ratio thing in a survival modal, so it does not quite match up here. But as a general scale, that is a huge effect for anything that goes through a log transform.

Interviewer #1: I see.

Participant #5: So this feels wide. Right now, knowing what you have said. Do I think that, sure, can I believe that your body stuff is going to change it a little bit? Sure. Is it going to make you a tenth as aggressive? That is a huge effect. In retrospect, I probably would have gone a little more. This is, maybe a third to three [Normal(0, 0.4)]? The 90% on this one? That sounds more reasonable, kind of.

Interviewer #1: Okay.

Participant #5: In the clear light of day.

Interviewer #1: Okay.

Participant #5: In general, the big one has to be centered around one. That would be centered around zero on this scale, one on this scale. It would be crazy to do anything else.

Interviewer #1: Okay. Cool. I guess we can move on to the next page, so close this tab and go back to the previous one.

Participant #5: This one?

Interviewer #1: Yeah, you can scroll down and hit submit.

Participant #5: This isn't going to break anything?

Interviewer #1: I don't think so.

Participant #5: Okay.

Interviewer #1: Is it taking you to the next page? It's not doing anything? Oh shit. Well, let me send you another link then.

Participant #5: I think this is...

Interviewer #1: I wonder if I...

Participant #5: Anything to do, there is just a button, it doesn't look like there is a link built into it.

Interviewer #1: Yes, but I...

Participant #5: Do I need to, I probably just need to...[crosstalk 00:18:20] fill this one out?

Interviewer #1: I just sent you another link. No, no, no, that is not the thing. I think I just need you send you the... I have been changing stuff on Github and I think that has been causing a problem.

Participant #5: Yeah.

Interviewer #1: Sorry about that.

Participant #5: No problem.

Interviewer #1: [inaudible] Okay.

Participant #5: Try this one? Number three?

Interviewer #1: Yes, you can close the other tabs if you want to.

Participant #5: Yes, okay. This one we're done with, this one we're done with. There we go.

Interviewer #1: Cool, so, this is loading. This page has three variations. The second one is what you have already seen, and this has the right label on it.

Participant #5: Yeah, okay, so this is intercept scale, response scale, and this is the fuzzy, yeah.

Interviewer #1: Okay. If you go up to the first one, this is the density on the parameter's scale. I don't think that needs any more explanation.

Participant #5: Yeah.

Interviewer #1: I guess we are looking at this visualization, do you think this information presented would affect your choice of priors in any way, and how would you use this information, if at all?

Participant #5: As opposed to the other one?

Interviewer #1: Yes.

Participant #5: On its own?

Interviewer #1: Yes, on its own, and comparing it to the other one.

Participant #5: It is clearly useful, right? I'm trying to think. I don't find this box the most natural, the way you interact with it. I am not sure why, though. It is two parameters on a 2D space, it seems like it should be.

Interviewer #1: How would you have preferred to work with it?

Participant #5: I don't know. The only other thing I can think of, from a scientific point of view, is two slide things, but it is not clear that is better. The structure of seeing the distribution is really useful. I do this kind of stuff fairly frequently. I am that grad student, so transforming to the log scale for Poisson is natural for me, but I don't think it would be for most people.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: Like I said, I did this math backwards in my head on the other one.

Interviewer #1: Mm-hmm (affirmative). Do you, I mean, in the other one you talked on, you converted the, you back-transformed it, and in your head you thought of things on this scale?

Participant #5: Because it was labeled that way, yeah.

Interviewer #1: Mm-hmm (affirmative), I see.

Participant #5: Which again, might just be me being pedantic. Yeah, but that is because this is how classical stat education works, right? You think the coefficients first, you don't think of the response first. I am not sure it is better. It is just what I was trained to do.

Interviewer #1: So you mentioned, when you fit other model figures, like a log transformed, or a logit transformed model, how do you think about your priors?

Participant #5: Poisson models, like a log transform, I am generally petrified of things blowing up.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: Right? Even just from simulating boring data, I know how easy it is to get ludicrously large numbers because of that exponential, and then the heavy tail of the Poisson. I tend to be really cautious about that, which is why pushing things back and forth through the log and the exponential is really central in my head.

Participant #5: On the logit scale, logistic regression, I tend to be less paranoid, because it is a zero or a one. It can't go that horribly wrong. Then I do keep that medical fact of that, there aren't that many huge effects in the world. There are some, but they are rare, right? I just know that I am probably not in that scenario, is the thing that stays in my mind.

Participant #5: The other one I know, I mean, what is wrong with these things, right? Logit models, like zero one data, is incredibly noninformative. It is literally one bit of the information. At the end of the day, there is just not a lot there. You do have to be a little more prior sensitive. You can't just be normal standard deviation a hundred.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: The same sample size, that can be okay in gaussian normal linear model if you get a lot of stuff out of it, but that is terrible in a logistic case because that is super wide and yo need a ridiculously large sample size to aim that.

Participant #5: In both of them I try to keep things small, but for different reasons.

Interviewer #1: I am just trying to get an understanding. When you are, just taking the case of a Poisson model, do you first start on the natural scale, and then transform it to the log scale to send them in, or do you go about like, this is what I wanted. I think the mean would be like, and then you exponentially transform it, and then see what it would look like, and go about it that way.

Participant #5: That is exactly what I am doing. If I am working with a collaborator, and analyzing an experiment that is done, or is about to be done, I will ask them how many things, with everything counted, would you expect, and I will back transform it. In my own work, I do a lot of stat theory work, so I do a bunch of simulations.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: I start in coefficient land, and I make data.

Interviewer #1: I see.

Participant #5: It depends on what I am trying to do. I will do both of them, depending on what part of my day it is.

Interviewer #1: I see. Okay.

Participant #5: I don't know, I have recently been working on some Poisson stuff, even writing test cases for software. Unless you are super cautious about it, you start making NANs and overflows really easily. Much more easily than I realized before I did this, and it has me scared.

Interviewer #1: Yes, I have definitely experienced that, especially, if you scroll down, I think we can look at the prior predictive distribution at the end. Yeah.

Participant #5: This one?

Interviewer #1: Yeah.

Participant #5: Yeah, these numbers are kind of terrifying, actually. This is a very sobering thought. How do I.... I don't even know how to make, there you go. That's how you make them small, you shrink everything. Yeah, I was, I am going to loathe myself for a second. I was at mean, standard deviation of 0.8, is what I picked early.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: I think this is what I picked. On this scale, this is incredibly dumb.

Interviewer #1: No, but you also chose a normal distribution.

Participant #5: Okay, it is less dumb. I take it back. Yeah, this is really sobering, actually, right?

Interviewer #1: Mm-hmm (affirmative).

Participant #5: This goes a long way to clarify this. I like this. I like the two colors, so you get to see both conditions. What knob is this, this is the intercept knob?

Interviewer #1: Yes.

Participant #5: Yeah, I really like this. Predictively, if you add both of them.

Interviewer #1: Side by side?

Participant #5: Yeah, so I could play with the intercept, and I could play with the orange versus green conditions.

Participant #5: What was the other thing I was going to say? On this, it would be useful for me to have 50, 80, 90, shaded regions.

Interviewer #1: I see.

Participant #5: I can tell you that this goes out here, but is this a lot? Is this a little? I don't actually know if I am worried about this.

Interviewer #1: So you want the central, or highest density interval, or something like that?

Participant #5: Yeah, I think so. I know there are people that hate on that stuff, because it is parameterization dependent. But, we are putting priors on the parameters, right? Get over yourself, it doesn't matter. You will always work within an actual parameterization, so just use it. That is kind of a hobby horse of mine, people who get really preachy about that, I don't think it is a real issue.

Interviewer #1: Okay, just again, how do you think this information presented in the visualization affects your choice of priors, and how are you using this information?

Participant #5: For these two? These top two?

Interviewer #1: No, the prior predictive one.

Participant #5: Well, I am going to contrast them. These two didn't... these two I could work through in my head because it is essentially a normal versus a log normal. I have a good sense of those in my head already.

Participant #5: This one is the one that really gives me the heebee jeebee's in a good way. Right when it first came up, and I saw these giant numbers, that did freak me out. I think it was a good thing. I didn't realize how bad this was until I saw how wide it was. Let's not use value words. How wide the implied distribution was until I saw it. That was really useful to me. I am so curious as to how terrible this was if I were worked on my own computer and really trying to play around with this and put effort into it.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: I would say, okay, what actually is the probability of this bucket, just histogram each of these. I see this little thing here. Is this one in a billion? Is this one in ten?

Interviewer #1: Okay, I see.

Participant #5: That would be interesting to me. This certainly catches my attention, but it doesn't answer the question of, okay, this looks heavier than I expected, but, really how heavy is it?

Interviewer #1: I see, yeah.

Participant #5: I think everybody is going to want to answer that for themselves differently.

Interviewer #1: Could you repeat that?

Participant #5: I probably would want thin probabilities, but I think other people might approach the problem differently, I'm not sure that is a generalizable response.

Interviewer #1: Interesting. So basically, you want to set an upper bound and say, this is the majority of the density, and you want to know how much density is being predicted outside of those bounds.

Participant #5: Yeah, right, I don't mind the theoretical possibility of the number 1,400 coming out, that doesn't bother me. But if that comes out ten percent of the time, or 0.001 percent of the time, is really really different.

Interviewer #1: Right.

Participant #5: And I can't get that from this kind of a plot.

Interviewer #1: Mm-hmm (affirmative). Okay.

Participant #5: I mean, I can kind of back it out. This is 20 hypothetical experiments, so this is five percent, very approximately. Which feels high, but I would look to know a little more surely.

Interviewer #1: Yeah. Okay, so, if you saw this visualization, what prior would you choose?

Participant #5: If I saw this only, or if I saw this and was allowed to play with my computer for a minute?

Interviewer #1: Let's say you saw this only.

Participant #5: Saw this only? That is super confusing. You can see how unstable that tail is, watching that axis is wild.

Interviewer #1: Yeah.

Participant #5: I would definitely go normal immediately, because those tails are terrifying. And, probably, here-ish [Normal3, 0.7)]. I am just trying to remember, the text said that 160 was not the craziest thing, and if that was the maximum possible number of squeezes.

Interviewer #1: Yes.

Participant #5: 130?

Interviewer #1: Yeah.

Participant #5: Yeah, so, this doesn't seem wild if we were to match. Anything along this side doesn't seem too crazy. This is a little much, but anything from here downwards, not wild.

Interviewer #1: Mm-hmm (affirmative), okay.

Participant #5: Again, just because by the time you get to 60 this feels like it is mostly done.

Interviewer #1: Yeah.

Participant #5: I just don't know how seriously to take some of these humps. I'm not 100% sure what is happening here, to be honest. [crosstalk] I don't know what these humps really mean.

Interviewer #1: It's sort of a problem with... we are using kernel density estimation?

Participant #5: Is that what's happening? Okay.

Interviewer #1: Yeah. If the model predicts one percent [crosstalk]

Participant #5: There was like 157 gaussians, then it puts them way over, yeah. That looks a little funny for this kind of data, but it is reasonable.

Interviewer #1: Yeah, for this model, and we are trying to figure out, generalize the visualization and we struggled with that.

Participant #5: Yeah, it's not crazy though. If you are seeing 157, you should be potentially okay though. Yeah, now that you say it is a galcian thing I know how to interpret the artifacts.

Interviewer #1: I see, okay, cool. Let's move on to the next page. And this button, that really does work.

Participant #5: Yes, it does.

Interviewer #1: So again, the first visualization is the parameter of probable density.

Participant #5: Sorry, I have a terribly old and slow computer.

Interviewer #1: That is okay, I think it's still loading.

Participant #5: Oh, crap! I shouldn't have refreshed that.

Interviewer #1: It is fine, it is a big html page, a few megabytes.

Participant #5: I just really need a new computer, but that is neither here, or just to close some of my many, many tabs. There we go, okay. So this is the coefficient in an ANOVA? Yeah, like I said, clearly centered around zero, for the reasons we talked about earlier, or one, depending on the scale.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: This is a really simple model, all things considered. Basically an ANOVA, so I can transform these in my head. If it were something more complicated, if it were a continuous response or something else, I think I would have a different response, but I not sure what that would be.

Interviewer #1: Interesting.

Participant #5: Just because this is a particularly simple case, right? It is a two group model, I can do the transformation in my head. This one, so this nob is going to separate the green and the blue, in theory? Yeah. Again, I clearly set them up just because I couldn't know the scientific context to be overlapping. That has got to be a mean zero situation.

Participant #5: And then, from this visualization, I do not have a huge response to like, and of the y axis, the scale perimeter.

Interviewer #1: I see.

Participant #5: Probably keep it high-ish. Oh, I guess that was in... That's too low.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: 90 looks too low to me. This kind of stuff I would be fine with. Pretty wide, normal distribution.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: 65 is too low, right, like. Based on the task, I want to at least admit the possibility of the theoretical maximum.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: The 130 number. This I would be fine with. It is kind of bizarre to me, actually, that [crosstalk] this does not seem....

Interviewer #1: What do you mean?

Participant #5: In general, my gut would have said, okay, do the distribution, plus an exponential, the scale, it's going to be super sensitive to the scale.

Interviewer #1: I see. Oh, I think I can explain that. So, when creating the property of probability, and this widget, we had to fix the... In the other one, we fixed them in different ways, we set it at zero, and all the variation was just because of the intercept. Here, we fixed the intercept at a very reasonable value and you can keep interacting with the mean difference... [crosstalk]

Participant #5: Because even the widest version doesn't get into the crazy numbers that we saw before, so yeah. So, in some sense, that is a little comforting to me that, okay, this is too low, but from here to here, it all seems reasonable enough. I like that, they're robust.

Interviewer #1: I see.

Participant #5: It feels robust, who knows if it really is.

Interviewer #1: I think, interesting.

Participant #5: Right? One of my consistent characteristics when making decisions. I am a boring conservative statistician, right? I don't like making decisions as part of an analysis, I like things that feel objective. But if I can convince myself that there is a wide range of values that give me, essentially, the same thing, then my decision doesn't matter that much.

Participant #5: The fact that this doesn't change wildly as I do this feels good.

Interviewer #1: I see. I think this variation can be misleading at times because it assumes that you have chosen a very exact prior on the intercept.

Participant #5: Yeah, I think my first reaction was, it was surprising how stable this was. And you are saying this is essentially with a fixed intercept.

Interviewer #1: Yeah because if you, let's say, I think we fixed the intercept at 3.5, so if you, that lead distribution with a scale of one, then the upper bound is around 5.5 times, and E to the power of 5.5 is 250, or something.

Participant #5: You are setting yourself up to blow out really quickly. I think that, in part, that is why it would be interesting to see both of these at the same time.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: The real, not the... I don't even know what to call it. Not the marginal effect, but the whole effect of the prior.

Interviewer #1: Hmm, interesting.

Participant #5: I think I would, based on what you're saying, and my previous intuition, this would not look as stable as it does. In the end, I would be back to being appropriately terrified of Poisson's.

Interviewer #1: That is fair. I think what you just said makes me think more about the limitations of a prior predictive density when you have multiple perimeters interacting with each other.

Participant #5: Oh yeah, super nasty. This is still, and this is a simple enough experiment. One factor, two cases, yeah. It would be really nasty. Like, if you had six cases and subgroups and all sorts of terrible things would happen. It's really hard, I don't know what to do with it.

Interviewer #1: Right. I mean, even if we put a multi-level model in there.

Participant #5: Yeah. Graphing that is hard. It's really hard.

Interviewer #1: All right, cool.

Participant #5: I don't know if this was helpful. I hope it was.

Interviewer #1: No this is great, this is very interesting. Especially since you have used such models before, and understanding how you usually do it in your own workflow. Wrapping up, I have a couple other questions. One is, when you affix models like this, what other information do you consider when choosing your priors?

Participant #5: Sorry, say that again?

Interviewer #1: In your past experience, when you, or even for this case, did you consider any other information when choosing the priors.

Participant #5: Like I said, really just the stuff you gave me, the rough mean and rough upper bound that you gave me. A general feeling that there are very few large effects in a log transform world, because they become too big. Other than that, not really, no.

Interviewer #1: Could we have provided any other information that you would have found helpful?

Participant #5: I still don't have a great sense of the experiment. It would be interesting for me to do it once.

Interviewer #1: I see.

Participant #5: Like I was saying, I tried to cap things at the maximum of 128, but that is the size of the balloon, that is not actually quite the right number. A human is going to stop at a lower bound, because of how the experiment works. A human upper bound might be 100. It would be interesting to know, what is the most a person ever did.

Participant #5: Looking at this now, actually, I see I made a mistake.

Interviewer #1: Can you elaborate on that?

Participant #5: This is the average number across conditions, was about 34, 35. Before, I was assuming that was the average in the baseline condition.

Interviewer #1: I see. Would that make a difference?

Participant #5: Probably not a huge one. Just assuming that the difference between conditions is probably less, not a huge effect.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: Right? I mean, I don't know this literature, but I can't imagine people are going to go from 60 to four based on how they are sitting. I don't think it is a huge effect.

Interviewer #1: Mm-hmm (affirmative), yeah.

Participant #5: You know, it was a mistake I made, or an incorrect assumption. Yeah, if I knew a little bit more about how large of an effect to expect, like I'm going to keep a mean zero here, but, [inaudible 00:46:50]. Like, some more to help equilibrate between these two.

Interviewer #1: I see.

Participant #5: Or this axis, yeah.

Interviewer #1: We did not do the study, and I am not super familiar with [crosstalk]

Participant #5: Yeah, yeah, I am just thinking of information. [crosstalk] I think crossing that by this like, there are no large effects heuristic.

Interviewer #1: Adding in psych usually most effects are, if you [crosstalk] standardize the effect sizes that is under 0.5.

Participant #5: Yeah, that is what I expect, too. Yeah, no. In terms of other intuition not really, no. It's a simple enough experiment, I don't think there are a huge number of pieces that I am missing out on. I recognize that by saying that, I've probably caused there to be things I'm missing out on, but.

Interviewer #1: Cool. So, just to present my final question, in your past, can you think of any instances, when choosing priors, any challenges that you faced?

Participant #5: Yeah.

Interviewer #1: Or any information that you had to consider.

Participant #5: Yes. Not so much for this kind of model. But as things get more and more complicated, picking appropriate summaries, particularly of multi-variate conditions is super tricky. I do work on financial models. The parameter that is like, oh, this is how much a person remembers something, and that gets plummeted all the way through to, how the stock market behaves. It is incredibly hard to tee those off against each other.

Participant #5: I only have observations of what the stock market looks like, not about people's thought processes.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: So it is really hard.

Interviewer #1: But you have variables in your model, predictors in your model.

Participant #5: Yeah, but they don't.... there is no one-to-one correspondence between them, and an observable aspect of the data. Everything depends on everything. You don't have the nice linear model type deal.

Interviewer #1: I see. [crosstalk]

Participant #5: Ultimately, a lot of that stuff comes down to, pick 15 things and just hope you're lucky and they all become reasonable at once. But that is not great.

Interviewer #1: Right.

Participant #5: The linear assumption of each parameter controls one thing that I can theoretically plot, as useful.

Interviewer #1: Yeah.

Participant #5: For what you are showing me.

Interviewer #1: Interesting, yeah. What would you [crosstalk]

Participant #5: What have I done?

Interviewer #1: Yeah, what have you done?

Participant #5: I've been, well I try to pass it off as principle, but it is really kind of lazy. I will fit a non-bayesian model to get an MLE type thing, and I will do it in some sort of sudo-robust way. For me, it is time series. So I will chop my data up into a bunch of different things, and get a bunch of different MLE's, and then I will use those as, really roughly, the scale of the prior.

Interviewer #1: I see.

Participant #5: I will use the MLE standard deviation, multiplied by ten. Just because that is going to match everything reasonably well.

Interviewer #1: I see.

Participant #5: But, I try to say, you can try to dress this up as empirical Bayes, yadda yadda yadda. But it is a little hokey. But it does work! It will find something that reasonably matches a lot of different aspects, because it is trying to optimize all of those aspects at once.

Interviewer #1: Mm-hmm (affirmative).

Participant #5: There's a mismatch between base stuff, and not base stuff, but it still seems to work a lot better than me trying to marginally set everything and hope for the best.

Interviewer #1: Mm-hmm (affirmative), I see. Is that work something you came up with on your own, or is it based off of some recommendation, or something?

Participant #5: I'm sure it is not original, but I can't tell you where I got it.

Interviewer #1: Mm-hmm (affirmative), I see. How long have you been doing [crosstalk]

Participant #5: That kind of thing?

Interviewer #1: Yeah.

Participant #5: I don't know. Quite a while. I think it is a quasi-formalization of a really standard practice, which is, just fit a bunch of these and see what numbers you get, and remember them. [crosstalk] And use that as a prior. That is kind of cheap, but that is essentially what it is.

Interviewer #1: I mean...

Participant #5: By chopping up the data into different sub-samples and...

Interviewer #1: Yeah.

Participant #5: I think that's all it really is. And it's just like, for some models that are really standard, I wouldn't need to bother with it, because somebody else has done the work of fitting it a bunch, but for a weird, new model, I will just fit it a bunch myself, and fake the experience, for lack of a better term.

Interviewer #1: I see, okay, cool. That is really interesting.

Participant #5: Yeah, I don't know if it works. [crosstalk] theoretical questions there, but the fact is, it works out well for me.

Interviewer #1: All right, awesome. I don't have any other questions for you. Do you have any questions for me?

Participant #5: No, I'm super interested in seeing when and where this work comes out, and I will keep an eye on it.

Interviewer #1: Yeah.

Participant #5: But otherwise, good luck.

Interviewer #1: Thank you, and thank you for all of your help. Thank you for participating in this survey, and also giving us an hour of your time for doing this. It's been super helpful.

Participant #5: Oh yeah, totally. You know, all in, together.

Interviewer #1: All right.

Participant #5: Okay, cool, well thank you.

Interviewer #1: Thank you so much, bye!

Participant #5: Bye.