**Alex Wiltschko:** 0:00

Just like there's a visual cortex in the back of your head and there's an auditory cortex kind of on the sides above your ears, several other places that process the senses, there's an area of the brain called the piriform cortex, and the piriform cortex is kind of underneath the jaw here and that's where smell gets processed. If you just rank the senses, you say how much brain matter is dedicated to each of the five senses. Vision is number one. Vision is so important for us. Smell is number two. When I looked that up I was surprised. Actually I would think that hearing or something would come to be number two. But according to the Allen Brain Atlas, smell is right behind vision.

**Craig Smith:** 0:36

Hi, this episode is sponsored by Salonis, the global leader in process mining. Ai has landed and enterprises are adapting, giving customers slick experiences and the technology to deliver. The road feels long, but you're closer than you think. You see your business processes run through many systems, creating data at every step. Salonis reconstructs this data to generate process intelligence a common business language With process intelligence. Ai knows how your business flows across every department, every system in every process. With AI solutions powered by Salonis, enterprises get faster, more accurate insights, a new level of automation and a step change in productivity, performance and customer satisfaction. Process intelligence is the missing piece in the AI enabled tech stack. Search Salonis C-E-L-O-N-I-S to find out more. Hi, I'm Craig Smith and this is I on AI. In this episode, we explore the fascinating world of fragrance with Alex Wichtsko, ceo of Osmo. Alex's lifelong passion for neuroscience, beginning at the University of Michigan through to his PhD at Harvard and his journey into the entrepreneurial world with Ventures. Alex is pioneering the intersection of neuroscience and technology, particularly focused on our olfactory experiences. From a childhood fascination with perfumes to advancing AI and scent detection and creation, Alex's story is a deep dive into the rich complexity of how we perceive the world around us. Join us as we unravel the mysteries of smell and its digital future. In this, I hope you find the conversation as fascinating as I did.

**Alex Wiltschko:** 2:50

My name is Alex Wichtsko. I'm the CEO of Osmo. In school I studied neuroscience at the University of Michigan and then I studied neuroscience again at Harvard, or I did my PhD, and then I ended up doing some startups. I went to Twitter and then Google Brain, where I worked on neuroscience again, and then I've spun out Osmo as a new company, a little bit more than a year old, and we do neuroscience as well. So it's been olfactory neuroscience all the way through. This is my one very, very deep obsession and it's been a straight line through basically the entire way.

**Craig Smith:** 3:33

That's great. And when did you get focused on olfactory senses, I mean?

**Alex Wiltschko:** 3:41

olfactory sense. Yeah, the olfactory sense. For me, the obsession started when I was very young. I think different people have different senses that they're attuned to. So some people just have that window of their house, the site window that lets in information to their insides really wide open. I don't not for vision, not really for hearing, but smell has always been this very vivid slice of reality for me. So just from a very young age I was always drawn to it, I was attuned to it, not that I knew how to talk about it or describe it or create them at all, it just was very interesting to me. And then I started collecting perfumes when I was in high school, roughly. And I grew up in a very small town in Texas and I was already a computer nerd. And then to add perfume collecting on top of that not necessarily a recipe for popularity, but these have been my obsessions and I've tried to combine those over my entire life. And I feel very fortunate to work at the intersection of computers and olfaction and I think there's just there's so much depth and richness here at this intersection and that's what I've dedicated my life to and that's what Osmo is all about.

**Craig Smith:** 4:57

And when you were saying whole factory, what are you referring to?

**Alex Wiltschko:** 5:01

I'm just punning with you. I mean, the space of smells is filled with puns, and so throughout our conversation this hour, and I'm sure we'll be able to drop some more.

**Craig Smith:** 5:08

Okay, you know, I know a little. I've talked to one other guy about the smell of versus. He called it in AI, a guy named Alexei.

**Alex Wiltschko:** 5:25

Kulakov, do you know him? I do. I'm a fan of his work, yeah.

**Craig Smith:** 5:30

Oh, okay, yeah, we talked about he was classifying volatile molecules according to their smell or predicting their smell using supervised learning. So tell us one other thing. I have to ask if you're particularly attuned. I spent many years in France and because I was a correspondent for a big newspaper, all the wine people sought me out and I had one guy in particular who would take me out to these meals and do the you know guess where the wine came from, trek, he and his colleagues, and it was remarkable that they could get within a few kilometers of where the wine came from. And he explained, in his view, that you know, the mind of a sommelier is like a card catalog, and and you just begin narrowing it down as you focus on different elements of the, essentially the odor right as much as the taste. And how does that? Maybe you can talk about the neuroscience. Well, first I wanted to ask you whether you're a wine connoisseur, but then how does that work in the cerebral cortex?

**Alex Wiltschko:** 7:07

It's a great question. So I enjoy wine. I would absolutely not pass the test that you've just described. So if I were to guess, I would be within maybe thousands of kilometers basically throwing darts. I don't have any special skill when it comes to wine, because I think it's exactly what getting really being talented at associating words or properties with smells is a matter of practice. I really don't think it's a matter of innate talent. Certainly, your nose has to be open. You can't have it closed via allergies or something anatomical that prevents you from smelling things. I've worked with perfumers and master perfumers over over the years, and what? What isn't the case is that they can smell vanishingly small amounts of stuff. Right, they don't have a lower detection threshold on average than the average person, but they have phenomenal abilities to associate smells with words and they have a phenomenal catalog of experiences with what the world smells like, and so their ability to use language and to reason about the contents of something that they're smelling is truly extraordinary to watch, and I've never spent time with a master sommelier, but I imagine that's the experience that you're getting as well. So if we were to break it down like what's happening there when you're smelling wine, even when you're tasting wine, because when you're, when you're tasting it, the liquid rolls off your tongue. You're experiencing the five or so different tastes that exist. But then, when you get to flavor, flavor is a collaboration of the tongue and the nose, and 90% of flavor is actually smell. What happens is what's called the chimney effect. Whereas liquid rolls down your tongue, down your throat, vapors are released that actually go backwards. So instead of smelling in through your nostrils, there's smells enter backwards from your throat into your nasal passageway and you're smelling. So the molecules that are in wine are there because of an entire history of a plant being grown, of the fruits being picked, of them being processed and fermented and placed in a bottle in age, and there are many, many thousands of different types of molecules in there, and the exact identities of those molecules and their ratios tells the story of how that sip of wine arrived into your mouth. And none of that's there by accident, none of it. It's all an indication of the history of that sip, right from its very birth, from the sunlight and the nutrients in the soil, all the way through how it was processed and stored to your enjoyment of it. And so to me it is not a surprise that if you were to look at the identities of those molecules, so forget the nose. If you were just to actually know, like, what the molecular structures were, that you could probably put together a case of oh, this is from southern Spain or from eastern France or whatever it might be, and it's this grape and it was processed in this way, because that has to show up in the data right, and the things that you do to living things and how you extract them and work with them. It's going to have an effect on the chemistry by definition. Now, the amazing part, the miracle, is that your nose can do that to some extent and that your nose can actually do that pretty well. And once you start to gain experience of what things smell like which is this incredibly powerful compression of one of the richest sources of information on the planet, which is what are the molecules in the air around us or in the things that we eat and drink it's incredible that that comes through and that we can even talk about it. So the neuroscience there, in terms of how we actually process that and how that rises to consciousness still a work in progress, oh no, but the fact that we can do it I just find to be miraculous and wonderful.

**Craig Smith:** 10:55

Yeah, yeah, and there's a particular part of the brain that's associated with, that's activated by smells, or does that move around?

**Alex Wiltschko:** 11:07

No, just like there's a visual cortex in the back of your head and there's an auditory cortex kind of on the sides above your ears, several other places that process the senses, there's an area of the brain called the pure form cortex and the pure form cortex is kind of underneath the jaw here and that's where smell gets processed. And actually if you go to a wonderful project called the Alan Brain Atlas and the Alan Brain Atlas is meant to map the different parts of the brain responsible for different things If you look at, if you just rank the senses, you say how much brain matter is dedicated to each of the five senses. Vision is number one. Vision is so important for us. Smell is number two. When I looked that up I was surprised. Actually I would think that hearing or something would come to be number two. But according to the Alan Brain Atlas, smell is right behind vision, which I think is phenomenal.

**Craig Smith:** 11:59

Wow, yeah, yeah, that's fascinating and I have to say, particularly for somebody like me who unfortunately has lost a sense of smell, oh no, yeah.

**Alex Wiltschko:** 12:12

Yeah, was it from COVID or a trauma? It?

**Craig Smith:** 12:15

happened around COVID, but it happened before I got COVID, so maybe I had some strain of COVID that I wasn't aware of. But anyway, yeah, I'm sorry to hear that I'm hoping it comes back, you know there's some tricks for bringing it back.

**Alex Wiltschko:** 12:36

There's no foolproof way that I've seen that definitely regenerates olfactory receptors. But what I've seen relatively consistently at least help a little bit, but no guarantees is to start smell training. So if you pick household items or bi-essential oils, just get a set of like 10 to 20 things that are consistently the same, consistently available, so like eucalyptus oil or your detergent or your dishwasher cleaner, whatever has a consistent smell that's been added to it, and you just try to train yourself and maybe blind yourself. So put it in canisters, that where you can turn it around and not see the answer, something like that, and then try to quiz yourself. That has helped people that I don't know if they've completely lost their sense of smell, but folks that have kind of a jumbled sense of smell after COVID, that training process has accelerated their recovery. Again, no guarantee that that's going to work, but it's the only thing that I've heard that's helped. So you might try that I certainly will.

**Craig Smith:** 13:39

I certainly will Let me know how it goes, yeah, yeah. So tell us about your work with AI and smell, and I'm particularly interested in the architecture of whatever AI model you're using. Is this straightforward supervised learning or something more complicated?

**Alex Wiltschko:** 14:06

Great, let's dig in. So I think the first point to touch on is like, why smell in AI? Like why use these techniques at all, given that we understand vision perfectly well before anything that resembled artificial intelligence Came on the scene, actually well before we had computers. And the answer is that the other senses have had what smell has not for a long time, and that is a map. So color has had RGB, three numbers that can help you map and do arithmetic on all the colors that we can see even more than we can see actually. And sound has had a map low to high frequency. We call it the Fourier basis, but that's the map of sound, right, and with it you can describe any sound and then also describe any music. So these maps have enabled the entire ecosystem of the digitization of these senses. So without a map you can't have a camera and you can't have JPEG and Photoshop and printers and displays. You can't have microphones and sound editors and speakers. You need a structured understanding of the sense in order to do anything else. Smell hasn't had this map, and it's not crazy that it hasn't, because smell is different in some important ways. The first is, if you just look at how complex. It is right at the beginning of the sensing process. There are three different channels of color roughly corresponding to red, green, blue in your eye, and then one kind of black and white channel, and in your ear there's really just one sensor which is kind of a loudness sensor, and it's a raid in your ear such that you get this map of low to high frequency. But smell has 350 distinct channels of information, right, and that's 100 times more complex in terms of the dimensionality of the input than vision. And so how are we going to make a 350 dimensional map with our map making tools from 100 years ago? The answer is no. We were never going to succeed at doing that. You can put the maps of color, the maps of sound, on a flat piece of paper or a globe, but you can't do anything close to that with smell. It's just too complex.

**Craig Smith:** 16:30

Let me just jump in that when you say 350 channels, are those different kinds of neural receptors, neurons, or are those regions? What distinguishes those 350 from each other? It's a great question.

**Alex Wiltschko:** 16:56

So the surface in your nose that senses smell is called the olfactory epithelium, which is like the retina but for smell, and in us it's about the size of a postage stamp and it's covered with olfactory sensory neurons that have sensing surfaces, and each olfactory sensory neuron only expresses one type of olfactory receptor, and so it's the same neuron but with different receptors in it, and there's 350 different types of receptors, and each of those receptors is sensitive to different parts of chemical space. Now the thing that's been mysterious about smell is we don't really know how to talk about what part of chemical space each receptor is sensitive to. That's been really at the root of the mystery is like what's the relationship between what a molecule structure is and what it's going to smell like when viewed through this sensory system? We just haven't known the answer to that. So that's where the 350 number comes from. Is these 350 different types of receptors that are expressed in neurons in the olfactory epithelium. So the issue is finding this map, and the map making tools of, however many years ago, weren't going to cut it, so that's where AI comes in. This is a pattern recognition problem, this is a data understanding problem, and this is exactly what the tools of artificial intelligence are built to do is to extract structure from very complicated, high dimensional data, and so that's what we have been doing, and that's what we've done is focus on this one problem to start, which is, if you can draw the structure of a molecule, can you predict what it's going to smell like? And this is something that lots of people have worked on before, including Alexei Kulikov. I love the work that he's done. The threshold that we crossed in the study we recently published in Science is we got really good at that prediction problem. In fact, we got so good that you'd prefer the predictions of our neural network that are just working with the digital structure of a molecule than a person that has access to the physical molecule, smelling it and talking about it. So our predictions have passed a kind of an odor-turing test, which is exciting because that means we can find totally new-fragments molecules from the enormity of chemical space, which is we can get into that topic of why that's interesting and important for society. But that's the threshold that we crossed with the science that we've done.

**Craig Smith:** 19:24

Wow, that's fascinating. So you're taking the physical shape of the molecule or the molecular composition, the different atoms?

**Alex Wiltschko:** 19:43

Yeah, you've got it exactly. What we're taking as input is the molecule phrased as a graph. So if you imagine each atom being a node and each bond being an edge, just like a social network graph, where, instead of friends being nodes and friendships being edges, it's atoms as nodes and bonds as edges, these are small graphs because the molecules that we can smell typically have 5, 10, 20 atoms in them, whereas social network graphs are big. These are small graphs. So we take the graph structure and we provide that to a neural network as input. You asked about the structure of what we use. We use supervised machine learning, so there's inputs, which are the molecular structures, and there's outputs, which is a perfumer description of what that molecule smells like. Those are the pairs that form training data for this particular neural network, and we then can run that neural network on new structures for which we've never smelled those structures and the type of architecture is called a graph neural network, and this was actually something that didn't really exist in a way that was easily usable, even for practitioners in the field, and when we started all this work, maybe five, six years ago, graph neural networks were just starting to show promise as an architecture that worked and of course things have evolved since then quite substantially. But this notion of using graphs as input to machine learning was actually kind of an interesting and new thing, because most of the inputs to machine learning usually are rectangles, right, it's images, grids, or it's text, it's strings of characters or tokens, and so having something that's a graph structure was actually a bit of a challenge to provide to machine learning. But that's been largely solved and we were grateful for the work that we're building on top of.

**Craig Smith:** 21:31

And so your system, the pairs that you're trained on, are you using? Is there a dictionary of smell for perfumiers? I guess they're called Perfumers Perfumers, yeah.

**Alex Wiltschko:** 21:52

Or are they sometimes?

**Craig Smith:** 21:52

referred to as noses, noses. Yeah, is there a dictionary that they use so that there's a consistent vocabulary? Otherwise you're into the subjective realm of semantics.

**Alex Wiltschko:** 22:08

Yeah, so the answer is yes, but there's no single taxonomy. So you mentioned wine before. There are odor wheels for wine. I don't know if there's one odor wheel for wine. There's a lot of overlap between different ones. So it's the same in perfume, where there are a lot of different taxonomies that cover most of what you're going to find in a fine fragrance or even in like hand soap or detergent, but won't cover everything, and generally different odor wheels disagree. What we did is we had to standardize this for machine learning. So we created we actually have a few taxonomies. The one that we use the most has about 130, 140 different words in it, and this is something that we created after a very careful study of all the words that we found used to describe the ingredients in the fragrance industry, and it turns out that 140-ish words really capture the bulk of what you find in the industry. Now we've since used a smaller taxonomy that we use for higher throughput labeling. So in the science paper we used a 55-word lexicon because that was what was economical to train people on very quickly. Now we have since worked on a much larger, more comprehensive taxonomy. That's meant to actually be the end all be all. It'll be evolving, but we have very large, comprehensive taxonomies as well. But you're completely right, you need to standardize, otherwise you don't have a target to shoot for. Now what turns out to be the case is you and I if we sit there with our noses and after you do your smell training and your smell recovers, hopefully you'd be able to do this in a few hours. We can learn to associate smells and words in a few hours. So when a perfumer says fresh cut grass, they mean something quite precise and there's actually a reference for that. There's a reference molecule called Cis3hexanol and if you smell something that smells like Cis3hexanol, it means you're smelling fresh cut grass and that's the term that they use. So it's not subjective at all in the sense that there are references. People can be trained to label, in the same way that you and I can take a crayon, a crayon box, and know okay, this is salmon, this is orange, this is mauve, this is black, this is white, whatever, and we can learn to get pretty good at that. And we might disagree about shades, but we can agree Modulo, color blindness and things like that we can agree.

**Craig Smith:** 24:31

And so take me through then to once you've trained the graph network, then what do you do? Just are you presenting, because the world of molecules, possible molecules, is endless. So yeah, how then do you start applying this to build your?

**Alex Wiltschko:** 24:59

odors You're right about that, which is, the space of possible molecules is effectively endless. It's huge the number of possible molecules that you can get to. What we did to first understand whether or not what we were doing was working was we needed to do a double blind trial. So we needed to take our GNN, our graph neural network, and predict the smells of molecules that nobody's ever smelled before. Some have never even been made before. And we needed to do this in a double blind setting so that we weren't fooling ourselves. We wanted to make sure that this was actually working and would generalize to new structures, to combinations of smells that hadn't been seen before. And so that's what we did, and this was a very close collaboration between myself, then my group at Google Brain, and Joel Mainland and his laboratory at the Menel Center. And what we did is we digitally sniffed hundreds of thousands of molecules, so we downloaded a catalog of molecules that we could purchase, so we could have synthesized, and we got rid of all the molecules, first of all, that were unsafe, that was an easy filter to run, and then we got rid of all the molecules that were too expensive or that would never have a smell, that are too big or otherwise some problem. And then we predicted the smell on what was left, and that was hundreds of thousands of molecules. And then what we did was we picked a set of 400 molecules that structurally looked nothing like what we'd trained the model on. It's a very, very different structurally. We predicted for these, or we selected these molecules to be structurally different from each other so that there was a diverse cloud of molecules, and then we also predicted their smells to be very different from each other and we kept the identities of these molecules secret and we actually we bought them or we had them synthesized. We now have these molecules physically, people could smell them. And then we presented these molecules to a panel that we trained double blind and we assessed OK, the best you can do is the average of the panel. For all things, in supervised machine learning, adjudication of a group of people or an average of a group of people is always the best. And then anyone individual has some distance to that panel mean. And the question was where is our model, where are our model's predictions in the pack of the panelists? Is it worse than the worst? Is it indistinguishable from folks or is it somehow superhuman? And it turns out for most of the molecules. Most of the time our model's predictions are closer to the panel mean than the median panelist. What that means is you'd prefer to ask our neural network what something smells like than any one individual panelist most of the time, which had nothing like that had ever happened before. That's superhuman cent prediction ability, which we were just astounded by. That this works.

**Craig Smith:** 27:52

And just going back to the 350. So that's built into the neural network. Those 350 categories are within the your odor map and you're placing a particular molecule somewhere in those, some combination of those 350 or yeah, related back to the 350.

**Alex Wiltschko:** 28:23

Great question. So this is a really interesting topic and actually is the location of a leap of faith that we took. So the way I was trained to approach this problem was first you have to understand the receptor biology and the first thing you should do is figure out okay, here's a molecule, which receptors does it activate? It turns out that information is not available to us for a bunch of reasons that we don't have to get into, so we, just as a field of olfactory science and of molecular biology, we can't actually access that information right now. Maybe we can in fibers. I hope we can. Thank you. We didn't wait for that information, but we trained a neural network that just took as input the structure and took as output our spoken or written rating of what these molecules smell like, and in between those is the entire human brain, the entire thing. So we're not breaking down the problem at all. That was the leap of faith. Now it turns out that all neural networks, in solving a prediction problem, build a map implicitly, and this is called an embedding, and I'm sure your listeners are familiar with the concept. So there is an embedding in our neural networks and the dimensionality of that embedding is about 250 dimensions. Now that's not a special number in any deep biological sense. That's what the engineering tells us it has to be. If it's much less than that, performance degrades. If it's much more than that, performance kind of plateaus. So 250-ish Now that's suspiciously close to that 300 number that I mentioned to you, and this kind of like few hundred number keep showing up in many different kinds of analyses that we do. So I think there's something deep there. I can't prove anything. I can't prove that there's a relationship between what our neural network, what the dimensionality of our embedding in our neural network is, and then there's true biology here. But our odor map is about 250 dimensional, and that's what we need to solve the problem.

**Craig Smith:** 30:18

Yeah, and then just to continue on the map, do you do then actually a 2D map or a 3D map in some rendering? Yeah, or are you using the term map sort of metaphorically?

**Alex Wiltschko:** 30:43

Well, it's a map, but in its true form it only lives in software and doesn't live in two dimensions. But we make visualizations of it in two and three dimensions and it's a two-dimensional shadow of a much higher dimensional object. So you're going to misinformation. But even when you do that, you see incredible structure. So one thing that popped out to us very early on, kind of shocked me actually, was how structured this map is, even when you view it in two dimensions. So what we found very early is there's a region of the map that has the floral label so that's one of the words that our perfumers use is floral, and there's a region of the map that has alcoholic and woods and fruit, and it turns out that inside of each of those regions lives all the specific examples of that label. So inside of floral is jasmine and rose and hyacinth and all those flowers. Inside of alcoholic is rum and wine and all those. We didn't tell it to do that. We did not tell the neural network to learn the fact that odor is intrinsically hierarchical, but it did, and it learned to separate different smells at very, very different parts of the map that are very different, and it learned to bring together smells that are actually quite similar. So all the flowers are together, all the fermented smells are together, et cetera. The woods are together. So we didn't tell it to learn that structure, but it's visible even in a two-dimensional projection of a 256-dimensional map.

**Craig Smith:** 32:14

Right, and then that would suggest that there's something, in your case, in the graph structure of these molecules and then in the physical world, in the shape of these molecules. Are there charge or something?

**Alex Wiltschko:** 32:39

Yeah, that's the part where artificial intelligence is. An incredible boon is we didn't know ahead of time what those patterns would be, but we suppose that there would be patterns, that there would be a relationship, and if you collect enough data and if you treat that data properly and you clean it and you build performant architectures, you can discover those relationships, which is what we did.

**Craig Smith:** 33:03

Yeah, now what are some of the applications I saw yesterday you had a press release about a mosquito repellent that was designed using this system. Can you talk about some of the Well before we do that? According to well, yeah, I mean one of the things I can see that you could do if you understand the structure of floral smelling molecules, you could create a new molecule that fits in that part of the map and have a new floral smell. Is that right? Oh yeah.

**Alex Wiltschko:** 33:51

You got it exactly. So that's the leading question, that's the segue what do you do with this? And the answer is exactly what you just said, which is you build new fragrance molecules and it turns out that we do need this. So the smells that are part of the products that we use and that some of which we love. I love the smell of the detergent that I use. It's what I've been using since I was a kid. I collect perfumes. I love those smells as well. Those are made by perfumers and they're made using blends of ingredients. Now, not all of those ingredients are going to be with us in the next five to 10 years, because some of them have issues. Some of them aren't as safe as we want them to be for some definition of safe either for personal application, they cause skin irritancy or environmental safety, where these molecules don't break down and return to the carbon cycle. So there's molecules that are very important for some of our memories, that need replacing, that need upgrading, and so what we're doing is we're applying our artificial intelligence platform to discover these molecules that not only smell great and are affordable to use so that they can be used in many products, but that are safe along every axis that we care about, looking into the future, for the justifiably rising standards that we have for the products that we use. So we're absolutely using this platform to do basically exactly what we validated it to do, which is discover new molecules from the enormous space of possible molecules. Now what we announced yesterday is our collaboration with the Gates Foundation to do something that seems like a surprising jump, which is not make molecules for people, but make that smell nice for people and make molecules that smell bad for insects, for mosquitoes particularly. There is a really interesting and beautiful link there that we discovered a few years ago, which is what we smell and how we smell turns out to be related to what insects smell and how insects smell, and it's not too crazy when you think about it. So we see in red, green, blue that's kind of the way we've divided up the world of color, turns out. Insects do too, and the way they do it, the way their eyes are structured, is wildly different, but the thing that's in common is the sun. The sun has been radiating visible light for a pretty long time, and that's what all life on Earth can evolve around the air that we breathe and the molecules that we need to detect have actually been relatively consistent and stable over evolutionary time, and so the thing that we can all evolve around is like what is there to smell? And the thing that's there to smell are molecules built and ejected by other living things flowers, plants, other animals, insects, et cetera and those molecules have been wafting through the air for hundreds of millions of years. So it turns out, if you get really good at smell and people, you can get pretty good at smell and insects, and if that's true, maybe we can design molecules that smell bad or repellent to insects, and it turns out that we can do that. Now we got a leg up. We got extra data that helps us solve this problem from a very, very interesting source which was hidden in Google Books. So it turned out that the United States Department of Agriculture had been testing insect repellents since 1942. And they started this because in the Pacific Theater of War, mosquitoes were a bigger problem than enemy combatants in terms of the health and the safety of our soldiers. So in the United States they just collected a lot of data on insect repellents and that data was put on library shelves and sat there largely dormant for generations, and it turned out it had been picked up and scanned by Google Books, and what we did is we gave new life to this data by taking these scanned books and then making it machine readable which was a large effort in and of itself, that doesn't happen automatically and then augmenting our AI platform with this data, and that turns out to work really, really well for predicting whether or not a new molecule is an insect repellent. So everything comes down to this one AI platform that we've built, which is understanding scent and molecules at the atomic and the molecular level, but it turns out to have really interesting applications commercially for fragrance and then for the public good and we also think, eventually commercially for designing new ways to control insects.

**Craig Smith:** 38:31

Wow, that's fascinating. So within the government data, you were able to identify particular molecules that were particularly repellent to mosquitoes. Is that the long and short of it?

**Alex Wiltschko:** 38:55

Yeah, we didn't. Actually, what we're not doing is taking the exact molecules that were tested 80 years ago and just doing new tests on them. What we're doing is using that data as training for our neural network, and then we are coming up with completely novel structures that we think can exceed even what was tested then. Now it's really good data. So the first quantitative description of how potent DEET is is in this data. It's the first time that that data was ever measured in 1942 or something around there. So there's really really strong repellents and then there's also weak repellents and, of course, for training data you want the full GANET. So that's what we provide is training to the same architecture, graph, neural network, and that's what we use to screen the space of all possible molecules that we can buy or we can synthesize. And then we of course make those real and then we test them with a partner in the Netherlands and I named TropicU, and then we've observed that that's actually working quite well.

**Craig Smith:** 39:59

Wow, and then is that being commercialized? Is this a?

**Alex Wiltschko:** 40:02

research project. It's in the early days, so what we've already demonstrated is that we can find molecules that are as or more potent than DEET. So we've hit that landmark, which is an enormous achievement on the part of the team, and what's next is to build molecules that not only are effective but are pleasant you might want to actually smell these things in a course that are safe, so that is a non-negotiable. Something that's very, very important to us is molecular safety, so that's the next phase of this. So we can find compounds regularly that we think could be the next generation in terms of efficacy. And now we're leveling up in terms of finding molecules that take all the boxes which is a much more challenging problem, but one that we're rising to to find molecules that could actually be commercial candidates or could be used in low and middle income countries to help stop the spread of insect-borne disease.

**Craig Smith:** 41:02

Yeah, wow, that's really amazing I've heard of. When I was talking to Alexei, we talked about artificial noses for various applications. Could this be applied to that, to a sensor that could give a readout of what it's smelling in, maybe in a, you know, a cave, if you're doing a rescue operation or something, or sensors even in homes to augment the carbon monoxide sensors, those sorts of applications?

**Alex Wiltschko:** 41:50

Absolutely. I mean the map that we've built. Yes, the models that we use to do molecular discovery take graph structure as input and then output human report of what things smell like, but in the middle of this model is a map. There's other types of data that we can project into the map. So it's not just molecular structure, it's other things. It could be chemical sensors. So our expertise in the company doesn't involve at Osmo, it doesn't involve creating new sensors. But if folks are listening to this podcast that are making new sensors, that want to partner and use our artificial intelligence capabilities to level up the hardware work that they're doing, we absolutely want to hear from you. We think that what we're building is a kind of missing piece for the field of electronic noses, of electronic chemical sensors and being able to interpret very challenging, sometimes noisy, sometimes complex signals from these devices. That's been one of the main challenges blocking progress in the field from my view, and so the fact that we have this map now might actually be an unlock in this space, and so we would love to partner with folks that are building the next generation of chemical sensors and electronic noses.

**Craig Smith:** 43:06

Yeah, wow. What are some of the other applications on the other end? I mean not sensing existing molecules and determining, you know, their toxicity, or something of creating novel molecules for specific applications. You mentioned perfume and I gave the example of coming up with a new floral smelling molecule. Are you working on that end as well?

**Alex Wiltschko:** 43:36

Yep. So that's our main focus as a business right now is designing the next generation of safe and performant fragrance ingredients, and it's not just perfumes, right? So I mean perfumes are a piece, but not a very big piece of the entire fragrance market. Think of all the places where smells are in the products that you use, and a lot of it is in home care, it's in home-senting, it's in personal care, it's in dish, soap and hands. It's everywhere. And those are constructed. Those fragrances are constructed from ingredients and we've identified types of smells and types of ingredients that we think we can help with that. We think we can improve their safety and improve their efficacy, and that is a major focus of the company.

**Craig Smith:** 44:23

Yeah, just as you're talking, I'm thinking of and forgive me, I'm a journalist but I'm sort of the dystopian side of it. You know the snack food industry has made a science out of developing taste combinations that are addictive. Could this be applied in the same way to fragrance that you? I mean all of it? You know TikTok is all about optimizing sort of dopamine releases. Is the same possible with smell, that you could develop smells that are so pleasant that people keep coming back to them?

**Alex Wiltschko:** 45:20

So the art of perfumery or of the in the flavor side. They're called flavorists. Their job is to blend ingredients to achieve a particular effect. What we focus on is building tools safe, performant, cost effective tools. It sounds like they have things figured out. What we're concerned about is making sure that the tools that go into really anything that is as fragrance or to some extent flavor, that those tools are safe and cost effective. So I don't think that we've got anything to add at the molecular level for what you're talking about. But our focus really is on can we create the best ingredients to safeguard the environment and our own bodies?

**Craig Smith:** 46:08

Yeah, and I'll go on to where the research is going after this. But another thing that occurs to me, as you were saying that, it's such a powerful sense for memory and we all have had the experience of smelling something that reminds us of our childhood, and that's a very powerful experience. Could you conceivably Identify that smell in your grandmother's basement that makes you go back to being a six-year-old or something?

**Alex Wiltschko:** 46:56

The answer is yes, that is possible. There are people that actually can do that now. In many ways you can imagine instead of taking a photograph. Photo is to light, as the word Osmo is to smell, which is why we chose that word for the company. You can imagine taking an Osmo graph of that smell. Once you're there, you're present with it, you can capture it, hold it, replay it whenever you want. That's what the future is going to look like. Wow, yes, we're building fragrance ingredients. That's important that we do that. That's the right move for our business. When we think about where scent is going, the arc that's in front of us is that there's a sense that we have as humans that hasn't been digitized yet. If you look at what it took to do that for a vision, it was about a 100-year process. It started with painting and then photography is really where it got started, and then accelerated with digital photography and then displays, printers, all that. We think that we can compress that timeline of 100 years into 10 for smell. The reason why we can do that is because we're standing on the shoulders of giants. All these technologies that photography had to wait for are here with us now integrated circuits and the internet and all the software, everything, exactly what you're talking about, I believe, is possible Taking an Osmo graph, capturing a smell, storing it, maybe manipulating it, combining it with other things, and then replaying it in a way that is personal, in a way that's instant and on demand. We see a path to that. That's something that we think about very, very deeply and that we're hard at work at working on the fundamentals, I would say, of how to enable something like that to exist.

**Craig Smith:** 48:50

How much. I'm thinking too about the entertainment applications, and already there are these immersive experiences that include smell. How much? I mean, of course you want to test that the molecules are safe. But presuming that the molecules are safe, how many molecules need to be released to trigger that kind of reaction in a human nose? I mean, is it a tiny tiny?

**Alex Wiltschko:** 49:36

amount. It's vanishingly small. The reason for that is because of what the sense of smell is for. In the first place, it's our frontline chemical detector. This is why when you smell milk, that's gone bad, that's actually totally fine and it's actually what you're supposed to do. But you shouldn't drink it, because what you're smelling you just get a little tiny sip of from this incredibly sensitive sensor and that's enough to get information about what to do about the world. It's like you can smell gasoline when you're filling up your car. You should not put it in your body, so you're getting just little, tiny, tiny, vanishingly small amounts of chemistry that you're just sampling. You're detecting, and it's safe to do so, and that's what smell is for.

**Craig Smith:** 50:27

Yeah, and so if you're in a room and there's a release of some molecules that trigger a certain smell sensation, do those molecules eventually degrade or do they land on the floor and over 20 years you would have this dust of different fragrances on your? What happens to these molecules after their release.

**Alex Wiltschko:** 51:01

It's a great question and that question is at the heart of some of these issues of molecular safety, particularly environmental safety. So the word that we use when asking about what happens to a molecule is biodegradability. So after the molecule has been experienced, what happens? So imagine a molecule with all these carbons and the bonds. Do they break apart and eventually become CO2 and trees breathe them in and respire them back to oxygen? The answer is yes for some molecules and no for others. So there are some molecules that are used in fragrance that seem to not ever break down, and that's problematic. That's something that we're working on. And there's some molecules that within a few days, will return to the carbon cycle, and that's the nature of life is things go into the trash or into the forest or wherever they end up, ending that phase of their life and then are recycled into a different phase of existence on this planet. That happens for most molecules is they break down, they transform and those carbons come back in some other way later. It's very, very important for molecules that are designed by people to design them to break down at a reasonable amount of time. Of course they have to be used, they have to be shelf stable. But once they're used and experienced and they're flushed down the drain or they've made it somewhere else, they must break down. That's called biodegradability. It's very important.

**Craig Smith:** 52:31

Yeah, so where are you going with this research, this system? So the company is Osmos. What's the system called?

**Alex Wiltschko:** 52:41

We call it our SENT AI platform, and it's really the engine inside of. Everything that we do is trying to always improve our map of SENT, improve the AI platform and to continue to augment it with new capabilities. So we've gotten quite good at all things in molecular engineering. So that's the core of what we do and what we focus on is can we predict the properties of molecules before we make the molecule? And there's many different properties that we predict and make. Some of them are, of course, what it smells like and how intensely it smells that kind of a thing. But in order to put a molecule on the market, all of these safety aspects are very important. So we focused on that as well. And, of course, we predict if a molecule is an insect repellent. So we're always augmenting our AI capabilities and we're doing that by generating data, and that data comes from many, many different places, but that's the engine that keeps us going. And then we've got phenomenally talented people that are generating the data, that are designing the experiments, that are designing the AI algorithms and all the infrastructure that's involved. It takes a velvety to do this.

**Craig Smith:** 53:54

And the platform that you're describing. It sounds like it wouldn't be a huge model, that you could deploy it at the edge. Is that right, or is this in a central cloud infrastructure?

**Alex Wiltschko:** 54:11

Yeah, For now it's in a central cloud infrastructure and that's the way that we can work the fastest. I can tell you that the amount of compute that's required for large language models, which is absolutely massive expenditures in electricity, that's the only way you can get those models to be as accurate as they are, as performant as they are. We're in a different regime. We're much smaller. It's not to say that our compute needs are small, because our cloud and our data needs are actually quite substantial because of the amount of data that we're bringing and manipulating and screening through, but the amount of electricity expended per model is much more economical.

**Craig Smith:** 54:48

Right, but could the model be deployed? We were talking earlier about if someone's building a sensor oh, I see what you're saying, we're just the sensor have to ping an API and make an API call.

**Alex Wiltschko:** 55:02

Just like there are now large language models that run on your laptop or your phone, you can always find a way to get a model with some trade-offs to run on many different devices. We absolutely would be able to do that. It's not something that we've done, as we haven't had a partner that we've gone that deep with on the chemical sensor side. On the electronic nose side, it's absolutely possible though.

**Craig Smith:** 55:23

Yeah, and so you're in the realm of supervised learning. There's all this talk right now around creating agents from large language models or world models. Could you put a combine this with a large language model so that you, on the one hand, in order to ask the system to identify a molecule that smells a certain way, and then maybe, on the other end, have it generate the molecule so that it could be synthesized?

**Alex Wiltschko:** 56:10

So my belief about what large language models can do and how they're going to be useful in this context is that we're going to see LLMs provide natural language interfaces to processes and tasks that previously required more complicated point and click or code-based interfaces. Now I personally don't think in the near term that large language models are going to learn how to do the very specific task of predicting at the molecular level what something smells like. The data is just not in the corporate right and in general, I believe in small, sharp tools to solve specific, targeted tasks. What LLMs have demonstrated an ability to do is use tools. So I think it's completely possible, and something that I think would be quite good from a productivity standpoint, to allow LLMs to grab onto the tools that we've built and mix and match them, and I think that would make our internal productivity higher once those kinds of systems are ready. It's kind of difficult to get those things to behave properly right now and actually be a productivity booster as opposed to just a fun thing to play with. It doesn't really do what you want it to, because, for instance, a hallucination that LLM might do for writing a history report is benign, but a hallucination for designing a new molecule can be bad, so we need to be rigorous in a way that you cannot enforce with LLMs right now, but I think using them as a glue to build a natural language interface to the tools that we built, yeah, that's very feasible and that might, in fact, be how we interact with these tools in the coming years.

**Craig Smith:** 58:02

Yeah, yeah. And then, on the other end, being able to describe if it's through an LLM or maybe through some other interface and have. I mean, there have been experiments with using LLMs to generate novel molecules. I'm sure you saw there was a famous case, I can't remember which model that generated 20,000 or 40,000 toxic molecules just is part of a test. But they can generate molecular structures in a few guard railets so that they're safe and air-resistant. Take care of the hallucination problem. Then you could turn that over to a wet lab for synthesis and come up. Is that how you imagine the workflow?

**Alex Wiltschko:** 59:04

Yeah, and again we're kind of speculating based on how well LLMs develop in the future. But what LLMs can do now is they can learn how to call out to another API, so you can train it with examples to say like, for instance, if you're trying to book travel, or if you're trying to schedule an appointment with your dentist or something If there's a schedule appointment with your dentist, api call. If there's a piece of software or a URL you can visit, you can teach LLMs to use that tool and in certain circumstances it knows. Okay, now it's time to use this tool and then take the results of it, wait for this API to return data and then use that in future processing. That's probably how these tools will interact with the CENT AI platform that we've built is that there's these small, sharp tools that have well-defined programming interfaces, and I believe it's completely reasonable to use LLMs as a natural language interaction layer where these tools will learn how to use our APIs, and that'll make us more productive internally.

**Craig Smith:** 1:00:17

Yeah, I see we're coming up against an hour. I don't want to run over in the event that you have a hard stop. I've been writing a lot about robotics and robotic sensors, and this could be another sensor on feeding into a robot's AI brain. Completely.

**Alex Wiltschko:** 1:00:43

And here's the thing one of my scientific heroes, or somebody I look up to very much as a fellow, named Zubin Garamani, and he used to run Google Brain, a really accomplished AI researcher, and he had a phrase which is you can't automate what you can't measure. And so if we want robotics or artificial intelligence writ large to do useful things with smells and with chemistry, we have to open that window for computation. And that is exactly what Osmo is all about is trying to take the perceptible slice of the chemical universe, this part of the chemical universe that matters to us, and process, understand, bring those signals to the world of computation, and I think that the impact of that is going to be it's difficult to imagine all the positive ways in which that's going to make us healthier and happier.

**Craig Smith:** 1:01:45

Yeah, this is a proprietary model, or are you open, sourcing it and building a company around the open source?

**Alex Wiltschko:** 1:01:54

The model that we built, the whole platform, is proprietary. So we've described the ways in which we built it and how we gathered the data and how we validated it, but the actual technology itself is Osmo proprietary.

**Craig Smith:** 1:02:06

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