From the Frontiers of Knowledge

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The Coupon Collector's Problem

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Periodiek

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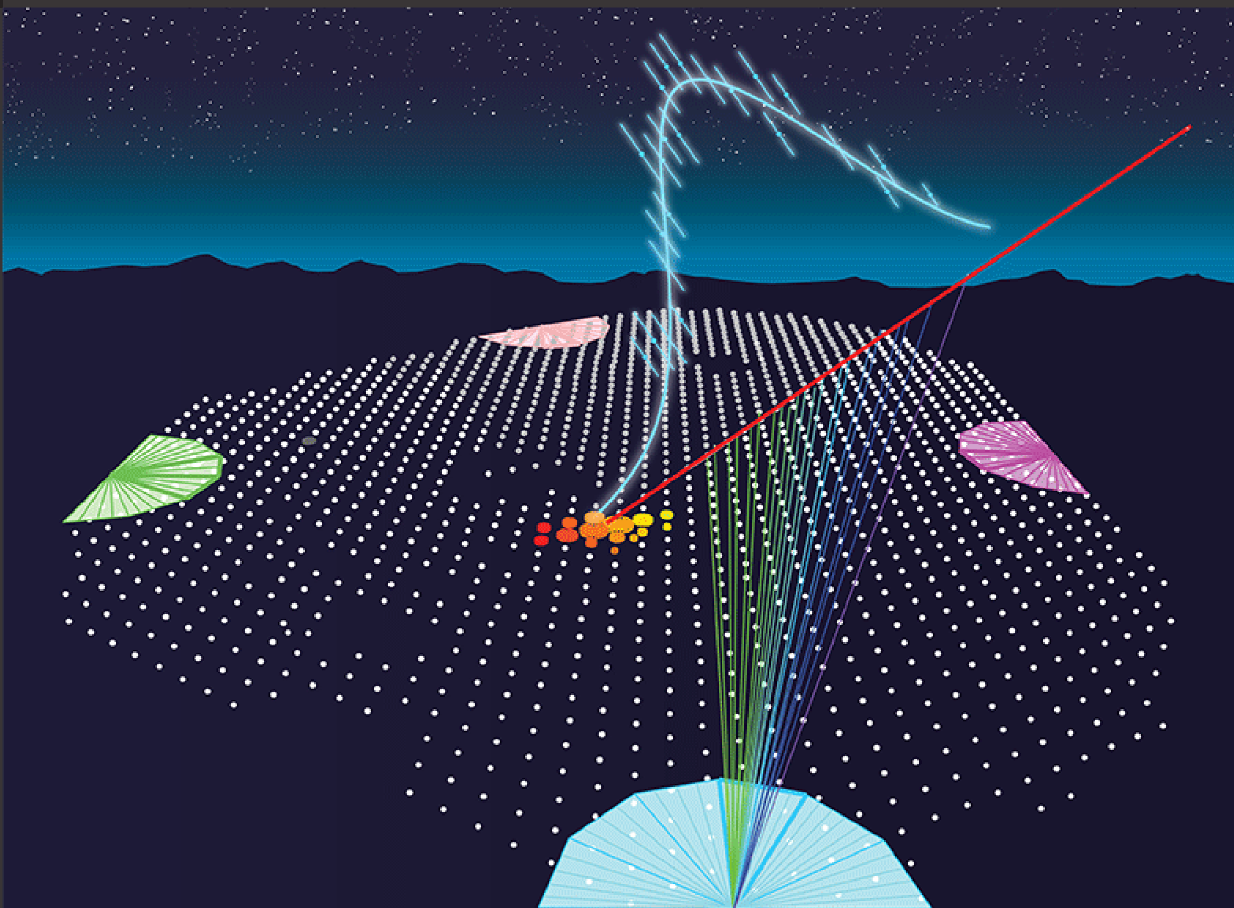
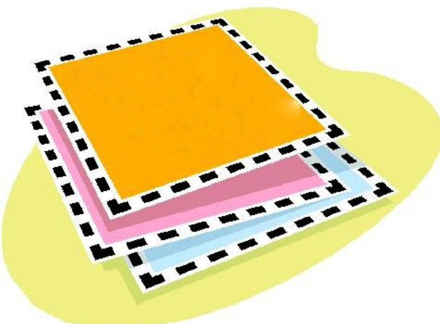


The Muon Problem

Why do our models fail? - p. 20 - 21

6 - From the board

A new year, a new board, a new chairman. Leander van Beek gives us his take on what the FMF has become, and how he experienced the first few months of his board year.

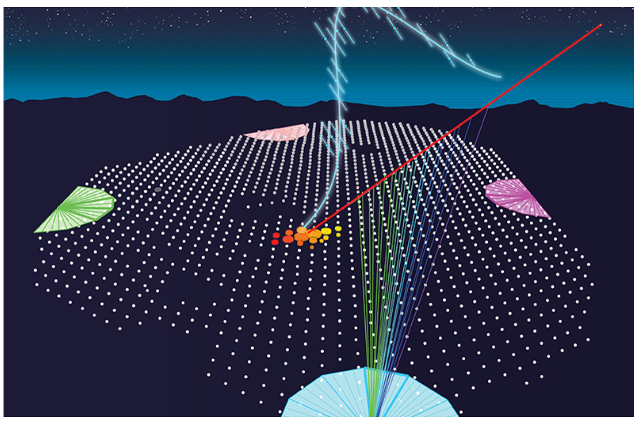


8 - The Coupon Collectors's Problem

Assistant professor Daniel Valesin from the Johan Bernoulli Institute tells us about a classical problem in probability theory. Given a sample containing a collection of n different coupons, how many sample trials do we have to take before we have every coupon from the collection?

20 - The Muon Problem

Periodiek editor Jonah Stalknecht discusses his bachelor thesis in a breathtaking article. He explains that the amount of muons created in cosmic ray air showers does not correspond to the predictions of our best models. Due to the high energies involved there is a lot of freedom to come up with new physical ideas.



In this Periodiek

Erratum
In the article "Building a Research Career at ASTRON" in the issue 2017-2, the two panels in Figure 3 were, unfortunately, swapped. The artist impression of the SKA dishes in the same acticle was made by Swinburne Astronomy Productions on behalf of the SKA Program Development Office.

From the Editor in Chief

Dear Periodiek reader, it feels good to say this for the first time as the new editor in chief. As I am writing this, we are in the middle of putting together the first Periodiek created by the new committee on a deserted university campus. I think it is fair to say that I have enjoyed putting this magazine together, although it took some effort and therefore I would thank the previous committee members for their great work.

When this edition reaches you, it is probably cold outside and therefore we've provided a recipe for a typical dutch winter dish called 'snert'. When you have cooked your very own batch of snert, you can enjoy it while reading the articles in this magazine or while making the puzzle in the back. The puzzle has a remarkable feature this time, which is that is actually solvable! I am saying this as in last edition, a mistake was made and therefore the puzzle was not correct.

Have fun reading!

-Gerrit van Tilburg

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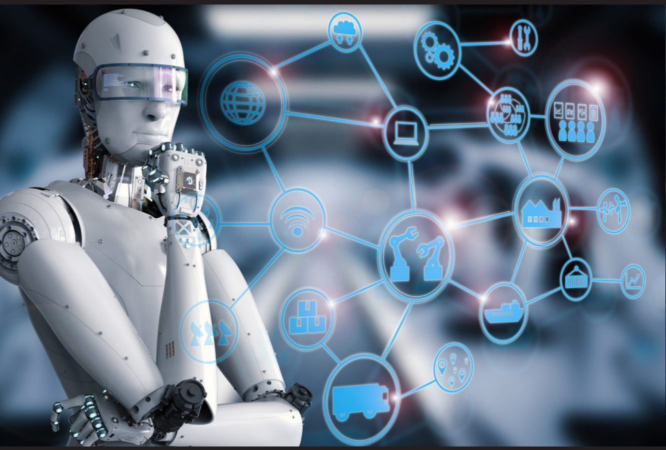
In the News



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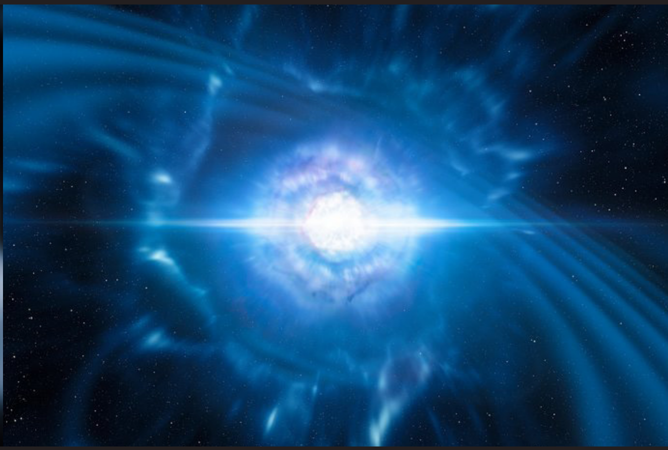


Space

Google's AutoML Trumps Human AI Engineers

Google's new AI project, AutoML, has managed to beat the best AI engineers at Google's disposal, after it created a more efficient and advanced machine learning software, just six months after its announcement.

The project focuses on *deep learning*: higher level of machine learning that is dedicated to mimicking human learning capabilities, and intends to democratise the field of artificial intelligence by supplementing the R&D of the few thousand AI experts in the world.

AutoML reportedly scored a record 82 percent at categorising images by their content, and was even more impressive on harder tasks such as marking the location of multiple objects in an image, taking the score of 43 percent versus the human-built system's 39 percent.

WIRED

If you want to know more about the link between machine learning and material science, read the contribution of the ZIAM to the from the frontiers of knowlege section in this issue (on page 12).

Merger of Two Neutron Stars Observed

Scientists have detected another set of gravitational waves; ripples in the fabric of space-time created by objects moving throughout the universe.

This is the fifth time that gravitational waves have been detected at the LIGO and Virgo observatories.

All four previous wave detections have come from the mergers of black holes, which are events that do not emit light. However, this time around, the waves were caused by the merger of two neutron stars: superdense leftovers of stars after they have collapsed. The merger caused the two objects to spiral around each other before smashing into one another. The result was a colossal fireball visible to light detecting telescopes at ESO, and other observatories around Earth.

This event is the first time that astronomers have observed both gravitational waves and electromagnetic radiation.

ESO, THE VERGE

New Leaps in CRISPR Research

CRISPR, the revelutionary gene-editing tool, has been the source of hype in the field of genetic and biochemical engineering for the past couple of decades.

The molecular scalpel is capable of altering or even deleting whole genes. Now, researchers at MIT and Harvard have announced that they have developed a more precise version of the DNA-editing tool: *base editing.*

The human genome contains six billion DNA letters. Base editing targets just a single base as it uses a modified version of CRISPR that is able to change a single one of these letters at a time without making breaks in the DNA's structure. This is a huge leap in removing point mutations, which are known to be involved in causing diseases. This also allows scientists to simply change a specific part, instead of moving a lot of DNA around.

This means that in a perfect world, CRISPR could possibly help 'delete' every faulty gene in the human body, making diseases and biological mortality a thing of the past.

NATURE, SCIENCE

Extracting Thermal Energy on the Nanoscale

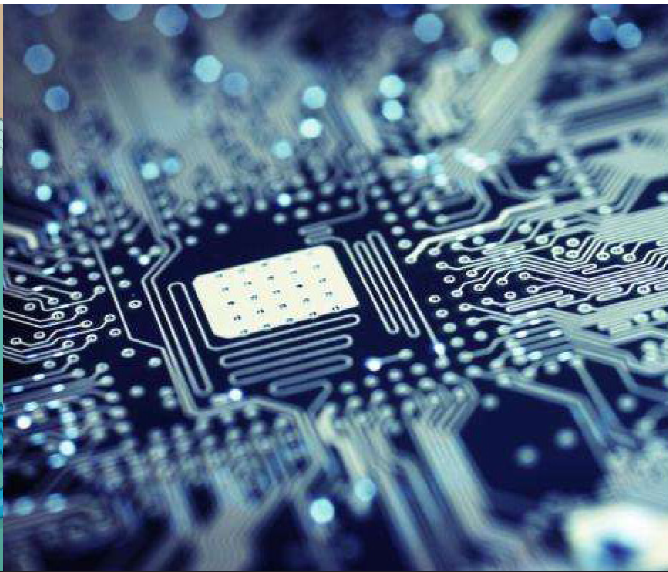
An international team of researchers from various institutes including the University of Glasgow and the University of Exeter in the UK, as well as from the ETH Zurich and the Paul Scherrer Institute in Switzerland, have found a new way to transform ambient heat into motion in nanoscale devices, a discovery which could open up new possibilities for data storage, sensors, nanomotors and other applications in the ever-shrinking world of electronics.

Their paper describes how they have created a magnetic system capable of extracting thermal energy on the nanoscale, using the concept of a gear known as a *ratchet*. They then turned magnetic energy into the directed rotation of the magnetisation.

These findings establish an unexpected route to transforming magnetic energy into the directed motion of magnetisation. The effect now found in the two-dimensional magnetic structures comes with the promise that it will be of practical use in nanoscale devices, such as magnetic nanomotors, actuators, or sensors.

NATURE MATERIALS

National Post



IoT

From the Board

AUTHOR: **LEANDER VAN BEEK**

Leander van Beek is the new chairman of the FMF. In this article, he tells about his experiences in the first board months.

A long time ago - 57 years, 11 months and 25 days, to be exact - something special happened. The moment was right, the stars were aligned in the right way, it was one in a million... That was the day that the FMF, the "Fysisch-Mathematische Faculteitsvereniging" was founded. Of course, a lot has changed since those days. Not just within our association, but also in the rest of the world. New technologies like the internet were developed, world conflicts were solved, celebrities were born, we reached the first celestial objects different from the earth and new fundamental physical concepts like string theory were discovered. Now I do not wish to compare these revolutions to the revolution that went around the FMF recently, but I can of course humbly tell you what happened.

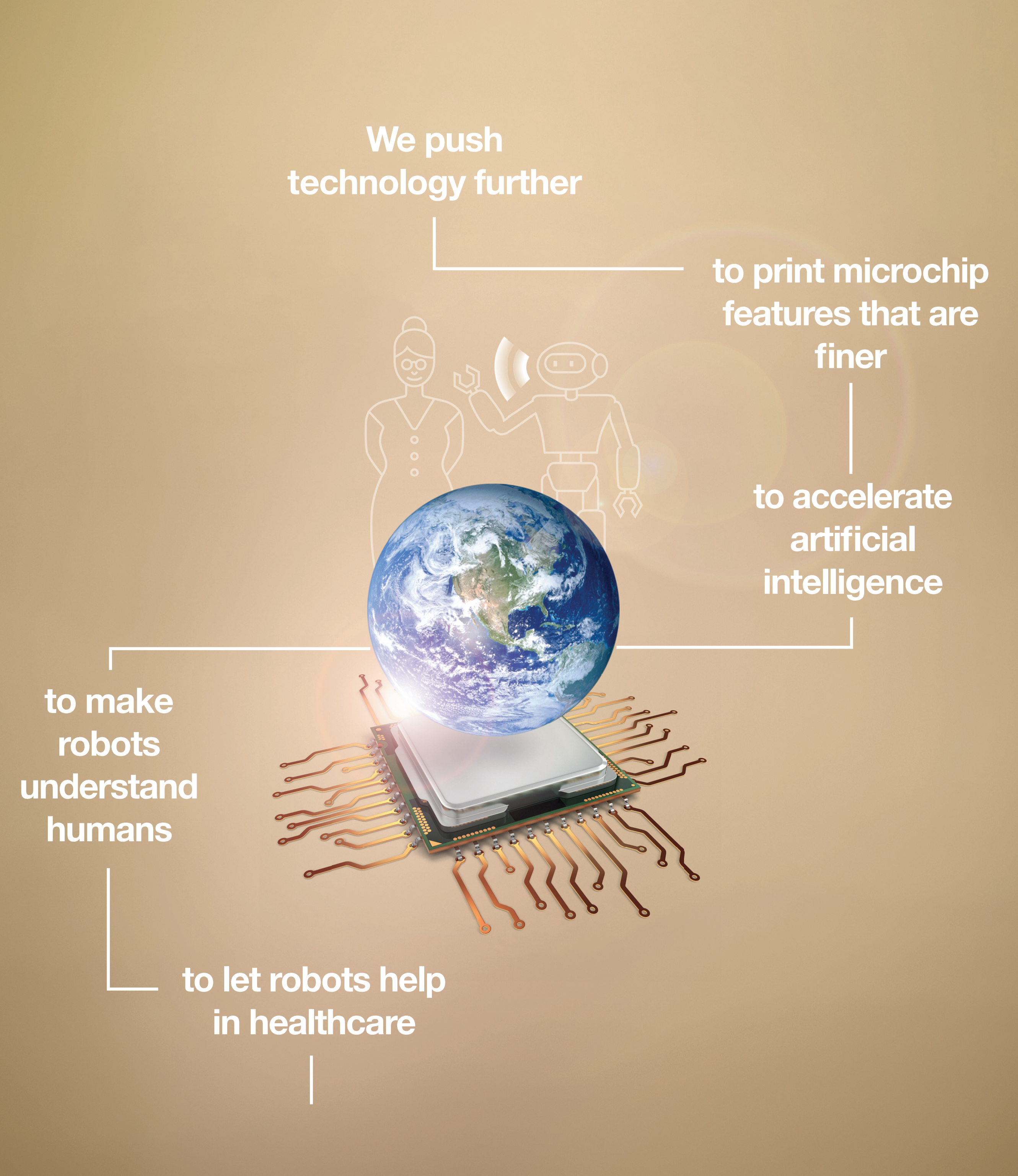
The start of the academic year is always a time of change. New freshmen arrive from all over the world, new plans and resolutions for this year are made, and the transition between boards is completed during the transition GMA in September. This year, it was time for the 58th board of the FMF to be discharged and time for the 59th board to take over. The transition ceremony during the GMA went pretty smoothly: thoughtful gifts were exchanged, beautiful board songs were sung and enlightening speeches on compactification were heard.

And then, our adventure took off. Literally. Imagine yourself barely awake, after the two hours of sleep that were had due the the celebration that was had after the GMA until many bars closed their doors. The bad longing for coffee is taking the better of you and by tradition, you do not know what you can expect when you open the NSFW for the first time in your official board year. You arrive at the faculty, early in the morning (*Bestuuur! Why are we out of coffee!?*) and open up the room. You smell... A forest. The sounds of birds are echoing throughout the room. You blink thrice to check if you're really seeing this - you are. The room has been completely rebuilt into a jungle. And you start wondering - does the previous board know what this room is? Is it a bar? Is it a jungle? Is it a study room? But, I digress. We take place in our regular seats, covered by branches and leaves. We know this is it; this marks the beginning of our official board year. And, although tired, we start cleaning up the NSFW while the first members arrive, congratulating us. This is it - our reign of the FMF has begun.

Now that two months are over, most of the new-academic-year-rush is behind us and we start to have some understanding of how to actually manage the association. Everyone is getting used to their position and although the rest of the year will probably be busy as well, this is when we can start incorporating our own ideas to make the association flourish like it never has•

FIGURE 1: Is it a bar? Is it a jungle?

FIGURE 2: The FMF´s very own Nobbie in his natural habitat: a messy NSFW


We push technology further
to print microchip features that are finer
to accelerate artificial intelligence
to make robots understand humans
to let robots help in healthcare

The Coupon Collector's Problem

AUTHOR: DANIEL VALESIN

A coupon collection consists of n types of coupons. Coupons are sold in sealed envelopes; each envelope contains a single coupon, which is equally likely to be of any of the n types. Every day we buy an envelope, until we have at least one coupon of each type, thus completing the collection. How long does it take for this to happen?

This is called the **coupon collector's problem** and is a classical problem in Probability Theory. It appears in A. de Moivre's first book on Probability, "*De Mensura Sortis*" or "On the Measurement of Chance", from 1708.

Let T_n be the number of coupons we buy until we complete the collection. This is a random variable, so we can of course not predict its value with certainty. However, can we say anything intelligent about it? For instance: certainly T_n is at least n, but would you expect that, when n is large, T_n is typically closer to n^2 or to 2^n?

We will become more informed by computing $\mathbb{E}(T_n)$, the expected value of T_n. To do so, let us define some auxiliary random variables. Let $t_{n,0} = 0$ and, for $m = 1, \ldots, n$, let $t_{n,m}$ be the total number of coupons we have bought until our collection has accumulated m different types. For instance, suppose $n = 5$ and we represent the five different types by the numbers 1, 2, 3, 4, 5. Assume that the types of the coupons we buy come in the following order:

$$1,\ 2,\ 1,\ 5,\ 3,\ 2,\ 2,\ 5,\ 3,\ 1,\ 4. \quad (1)$$

We then have $t_{5,1} = 1$, $t_{5,2} = 2$, $t_{5,3} = 4$, $t_{5,4} = 5$, and $t_{5,5} = 11$. Note that $t_{n,1}$ is always one and that $t_{n,n} = T_n$. We can express T_n as the result of a telescoping sum:

$$T_n = t_{n,n} = (t_{n,n} - t_{n,n-1}) + (t_{n,n-1} - t_{n,n-2}) + (t_{n,n-2} - t_{n,n-3}) + \cdots + (t_{n,1} - t_{n,0}).$$

Each term of the form $t_{n,m+1} - t_{n,m}$ represents the amount of coupons we had to buy to make our collection go from having m distinct types to having $m+1$ distinct types. Think of it this way: after time $t_{n,m}$, each new coupon we buy is an attempt (or **trial**) to obtain a type distinct from the m types we already have; the trials are independent and the probability of success of each of them is $\frac{n-m}{n}$. Then, $t_{n,m+1} - t_{n,m}$ is the number of trials needed until we have a success. In the language of Probability Theory, this means that $t_{n,m+1} - t_{n,m}$ follows a **geometric distribution** with parameter $\frac{n-m}{n}$,

$$t_{n,m+1} - t_{n,m} \sim \text{Geometric}(\tfrac{n-m}{n}).$$

The expectation of a Geometric(p) random variable is $1/p$ (if the probability of winning the lottery is 10^{-8}, then the expected number of times we have to play until winning is 10^8). We thus obtain

$$\begin{aligned}\mathbb{E}(T_n) &= \mathbb{E}(t_{n,n} - t_{n,n-1}) + \mathbb{E}(t_{n,n-1} - t_{n,n-2}) + \cdots + \mathbb{E}(t_{n,1} - t_{n,0}) \\ &= \frac{1}{\frac{n-(n-1)}{n}} + \frac{1}{\frac{n-(n-2)}{n}} + \frac{1}{\frac{n-(n-3)}{n}} + \cdots + \frac{1}{\frac{n-0}{n}} = n \cdot H_n,\end{aligned}$$

where $H_n = 1 + \frac{1}{2} + \frac{1}{3} + \cdots \frac{1}{n}$ is the sum of the first n terms of the harmonic series. As you may know, H_n is quite close to the natural logarithm of n, $\log(n)$ In fact,

$$\lim_{n\to\infty} (H_n - \log(n)) = \gamma,$$

where γ is called the Euler-Mascheroni constant, $\gamma = 0.5772\ldots$.

We have thus shown that on average, to complete a collection of n distinct types of coupons, we have to buy about $n \cdot H_n \approx n\log(n)$ coupons, which is surprisingly little, just a logarithmic factor above the minimal required amount, n.

The next natural question to ask is: how well does this expected value reflect the behavior of T_n? We will now argue that if k is a large number, then T_n is very likely to be less than $n\log(n) + k \cdot n$. This means that, after we have bought $n\log(n)$ coupons, if the collection is not yet complete, then we can be quite confident that it will be complete once we buy the (comparatively smaller) additional quantity of $k \cdot n$ coupons.

In order to give the argument, we will need some more auxiliary random variables. For each coupon type $i = 1, \ldots, n$, we let

$$\tau_{n,i} = \begin{array}{c}\text{number of coupons we buy until} \\ \text{the first coupon of type } i \text{ shows up.}\end{array}$$

For example, in (1) we have $\tau_{5,1} = 1$, $\tau_{5,2} = 2$, $\tau_{5,3} = 5$, $\tau_{5,4} = 4$, $\tau_{5,5} = 11$. Note that T_n is the largest among the values $\tau_{n,1}, \ldots, \tau_{n,n}$, that is,

$$T_n = \max_{1 \le i \le n} \tau_{n,i}. \qquad (2)$$

You can convince yourself that

$$\tau_{n,i} \sim \text{Geometric}\left(\tfrac{1}{n}\right),\ i = 1, \ldots, n. \qquad (3)$$

For a fixed type i, what is the probability that $\tau_{n,i} > n\log(n) + k \cdot n$, that is, that it takes more than $n\log(n) + k \cdot n$ purchases until we get a type-i coupon? For this to happen, every purchase we make, from the first to the $n\log(n) + k \cdot n$, has to be of a type different from i; this has probability

$$\left(1 - \frac{1}{n}\right)^{n\log(n)+k\cdot n} \le e^{-\frac{1}{n}(n\log n + k\cdot n)} = n^{-1} \cdot e^{-k},$$

where we have used the inequality $1 - x \le e^{-x}$. We then estimate as follows (using the inequality $\mathbb{P}(A \cup B) \le \mathbb{P}(A) + \mathbb{P}(B)$):

$$\begin{aligned}
&\mathbb{P}(T_n > n\log(n) + k \cdot n) \\
&= \mathbb{P}\left(\max_{1\le i\le n} \tau_{n,i} > n\log n + k\cdot n\right) \\
&= \mathbb{P}\left(\{\tau_{n,1} > n\log n + k\cdot n\} \cup \{\tau_{n,2} > n\log n + k\cdot n\}\right. \\
&\left.\cup \cdots \cup \{\tau_{n,n} > n\log n + k\cdot n\}\right) \\
&\le \sum_{i=1}^{n} \mathbb{P}\left(\tau_{n,i} > n\log n + k\cdot n\right) \le n \cdot n^{-1} \cdot e^{-k} = e^{-k},
\end{aligned}$$

which is very small if k is large.

Another way to express what we have just proved is: the **fluctuation** $T_n - \mathbb{E}(T_n) = T_n - n \cdot H_n$ has order of magnitude at most n (at least when it is positive). In [1], the Hungarian mathematicians Paul Erdős and Alfréd Rényi proved something much more refined. Namely, they proved that we can write

$$T_n = n \cdot H_n + n \cdot \mathscr{E}_n, \quad \text{that is,} \quad \frac{T_n}{n} = H_n + \mathscr{E}_n,$$

where $\mathscr{E}_n$ is a random variable whose distribution *converges to something* as n tends to infinity.[1]
What is this limiting distribution? It is called the (standard) **Gumbel distribution** and has the funny-looking probability distribution function

$$F_{\text{Gumbel}}(x) = e^{-e^{-x}},\ x \in \mathbb{R}.$$

Saying that $\mathscr{E}_n$ converges in distribution to this means that, for any x,

$$\mathbb{P}\left(T_n \le n \cdot H_n + n \cdot x\right) = \mathbb{P}(\mathscr{E}_n \le x) \xrightarrow{n\to\infty} F_{\text{Gumbel}}(x),$$

which is the statement you will find in Erdős and Rényi's paper.

We will now leave aside coupon collecting for a moment to say a few words about the Gumbel distribution. This is an important distribution in Extreme Value Theory. In a nutshell, EVA is the study of the occurrence of abnormal outcomes when a certain natural observable is being measured repeatedly. If the previous sentence tells you little, consider the following example: every day we measure the level of a river; we are interested in describing the frequency with which we should expect the river to rise so much as to produce a flood.

Here is a quick toy model to illustrate how the Gumbel distribution arises. Let $X_1, X_2, \ldots$ be independent random variables representing measurements of something along time (in the example given above, the X_i's would represent the daily measurements of the level of the river). Assume the X_i's follow the **exponential distribution** with parameter 1, that is, they have the distribution function

$$F_{\text{Exp}(1)}(x) = 1 - e^{-x},\ x \ge 0.$$

1 If you are familiar with the Central Limit Theorem, this is a similar type of result as that: the "normalised" random variable $\frac{T_n - \mathbb{E}(T_n)}{n}$ has a distributional limit. However, unlike the CLT, here the limit is not Gaussian.

Then, consider the random variable

$$Y_n = \max_{1\le i\le n} X_i, \tag{4}$$

that is, Y_n is equal to the largest among the values $X_1,\ldots,X_n$ (so that in a way, Y_n corresponds to the most "extreme event"). The probability distribution function of $Y_n - \log(n)$ is given by

$$\begin{aligned}\mathbb{P}(Y_n-\log(n)\le x) &= \mathbb{P}(X_1,\ldots,X_n\le \log(n)+x)\\ &= \mathbb{P}(X_1\le\log(n)+x)^n\\ &= [F_{\mathrm{Exp}(1)}(\log(n)+x)]^n\\ &= \left[1-e^{-(\log(n)+x)}\right]^n\\ &= \left(1-\frac{e^{-x}}{n}\right)^n \xrightarrow{n\to\infty} e^{-e^{-x}}\\ &= F_{\mathrm{Gumbel}}(x),\end{aligned}$$

where we have used the well-known limit $\lim_{n\to\infty}(1+\frac{a}{n})^n = e^a$. That is, $Y_n-\log(n)$ converges to the Gumbel distribution.

Coming back to the coupon collector's problem, we will now give a heuristic explanation to the appearance of Gumbel-distributed fluctuations. The question is: what does collecting coupons have to do with Extreme Value Theory? The connection will come from relating equation (4) to equation (2) divided by n,

$$\frac{T_n}{n} = \max_{1\le i\le n}\frac{\tau_{n,i}}{n}.$$

That is, we want to establish a similarity between Y_n (= the maximum among n exponentially distributed random variables), and $\frac{T_n}{n}$ (= the waiting time to complete a collection of n coupons, divided by n). To this end, we must establish a similarity between X_1, ..., X_n and $\left(\frac{\tau_{n,1}}{n},\ldots,\frac{\tau_{n,n}}{n}\right)$.

Two problems arise. Problem 1: the distribution of the X_i's is not the same as the distribution of the $\frac{\tau_{n,i}}{n}$'s. However, we now claim that, due to (3), these two distributions are similar when n is large. Indeed, it is a simple exercise to show that, if we take a Geometric$(\frac{1}{n})$ random variable and divide it by n, then the resulting random variable is close to Exponential(1).[2]

Problem 2: the X_i's are independent, while the $\frac{\tau_{n,i}}{n}$'s are not. To see that the $\frac{\tau_{n,i}}{n}$'s are not independent, consider the case in which there are only two types, $n=2$: if we are informed that $\tau_{2,1}=2$, that is, that type 1 appeared for the first time as the second purchased coupon, we are then forced to conclude that $\tau_{2,2}=1$. You will probably agree that this becomes less of an issue when n is large: then, the value of any one of the $\tau_{n,i}$'s will give us much less information about the others. Actually proving that this heuristic "asymptotic independence" implies a convergence to the Gumbel distribution is technically challenging.

As you can imagine, this is not where the story ends. Already in [1], the authors considered a variant of the problem where we are not only required to complete a collection, but rather, to accumulate at least r coupons of each type, where r is some positive integer. Other variants of the problem (including the situation in which the types are not equally likely to appear) and interesting connections to other well-known probabilistic problems were studied in [2]. There are numerous other works on the coupon collector problem.

A direction of research that I find especially interesting is the generalisation of these ideas to Markov chains and random walks (see for instance [3], [4], and [5]). Let me finish with a flavor of the type of result that can be achieved. Suppose we have a deck of N cards, which we sequentially shuffle (imagine a simple shuffling rule, such as: in each step, exchange the positions of two randomly chosen cards). We proceed until all the $N!$ possible orderings of the cards have appeared at least once. In [3] it is proved that the number of shuffles we need is $(N!)\log(N!)+(N!)\mathscr{E}_N$, where $\mathscr{E}_N$ is a random variable converging to the Gumbel distribution•

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[5] David Belius. Gumbel fluctuations for cover times in the discrete torus. *Probability Theory and Related Fields*, 157(3-4):635-689, 2013

2 Intuitively, this approximately (when $n\to\infty$) describes an Exponential(1) random variable as the time it takes to obtain the first success if we perform trials such that each trial (a.) has success probability $\frac{1}{n}$, and (b.) only takes $\frac{1}{n}$ units of time. There is a double limit here: success is becoming increasingly rare, but things are also happening increasingly fast.

PHILIPS

Materials That Can Learn

AUTHOR: MART SALVERDA, PHD

The Faculty of Science and Engineering is about to inaugurate the Groningen Center for Cognitive Systems and Materials (CogniGron), whose goal is to unite the existing expertise in Materials Science, Physics, Computer Science, Artificial Intelligence and Mathematics to develop a cognitive computer that is able to deal with the huge amounts of useful data that we generate. This has to be a computer that can recognise patterns and classify heterogeneous data without requiring the power of a supercomputer, as we do now. In order to achieve this, it is crucial that we are able to incorporate 'materials that can learn' into the computer's hardware.

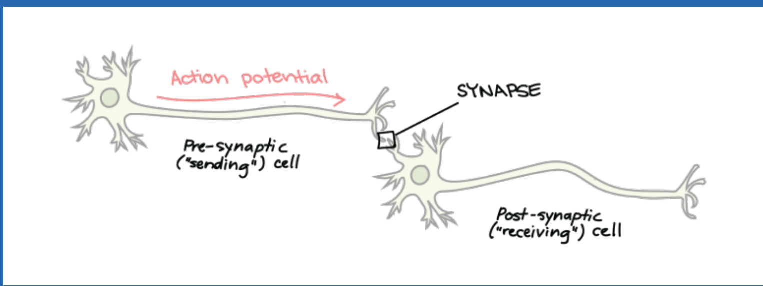


FIGURE 1: Sketch of two biological neurons (Image: khanacademy.org)

AlphaGo

In 2016, a supercomputer called AlphaGo won a match of the board game Go (which is considered to be the most complicated board game of human origin) against the best player in the world, Lee Sedal. In this game the number of possibilities is so large that a brute force method, in which all the possibilities are computed (this is how Gary Kasparov was beaten in a game of chess in 1996), would be unfeasible. To be able to play the game, AlphaGo made use of deep learning algorithms and was trained in advance.

Machine learning algorithms emulate in some aspects the way the human brain processes information. This is found to be very useful not only for playing board games, but also in other areas such as recognition of speech, handwriting, number plates or image contents, translation of text and fast-approaching future applications such as self-driving cars and autonomous robotics.

However, when comparing both contestants, the match of Go does seem a bit unfair: while Lee Sedal's brain uses only about 20W of power, AlphaGo is estimated to require 1MW to operate: 50.000 times more power! Note, that this was only to play Go. They would never put a 1MW computer in every self-driving car! So, how is it possible that our brain can perform so well at only 20W?

The brain

Let's first look at the main components of the brain: the neurons, which are connected to each other by synapses. The human brain has approximately 10^{11} neurons and every neuron is typically connected to some 5000-10000 other neurons (so there are about 10^{15} synapses). Information is carried in the form of electrical pulses (or spikes) that are transported through the synapses. Even though this happens by means of complex electrochemical processes mediated by ions and large molecules (so-called neurotransmitters) and, therefore not the subject of this contribution, one can simply consider that each synapse provides a certain resistance to the transfer of signals between two neurons. The relative resistances (or weights) of all the synapses

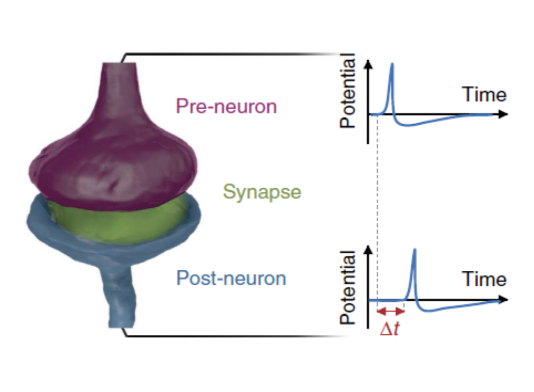
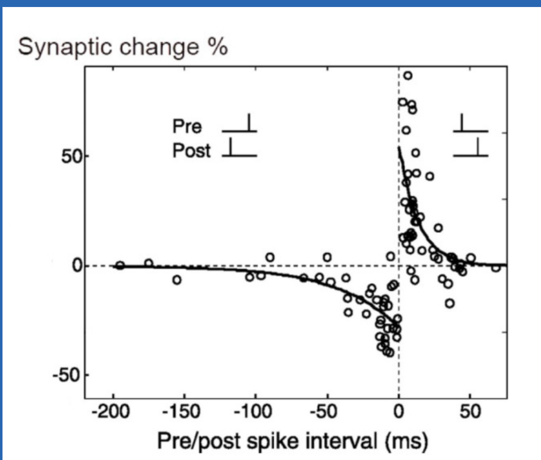


FIGURE 2: Biological synapse and spikes (above) [3]; characteristic STDP behaviour of synaptic weight (below) [5]



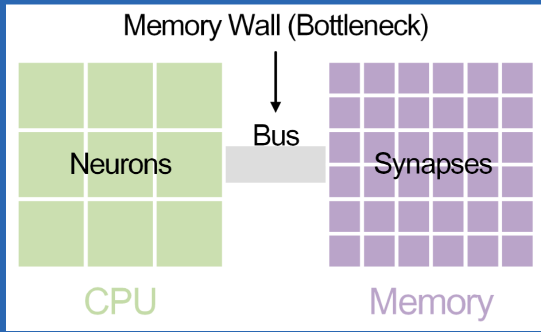
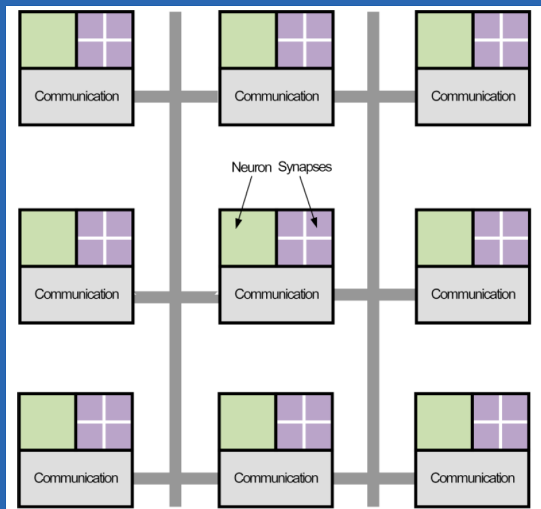


FIGURE 3: Conventional computer architecture (above) and parallel, more brain-like architecture (below) [2]



in the neural network determine the paths along which the information is transferred.

The neuron integrates all the signals it receives from the other neurons it is connected with. When its own potential reaches a certain threshold, it will produce a spike of its own. The synaptic weight can be adjusted by the activity of the two neurons on either side of the synapse. If the pre-neuron fires a spike right before the post-neuron does, it might be that there is a causal relation between the two events and as a result the synaptic weight increases (resistance decreases) so that more signal is transferred through that particular channel next time. In contrast, if the reversed order occurs the resistance increases. This behavior is captured in Figure 2 and is called *Spike-Timing Dependent Plasticity* (STDP). When synapses change their resistance, making certain paths easier for the signal to pass along, is when the brain is actually learning.

Even though the signals in our brain are quite slow (10^{-3} s) compared to those in the computers CPUs (10^{-9} s), the brain performs many calculations in parallel all over the brain, in contrast with computers which can only perform one computational task at a time. Together with the interconnectivity, this allows for very fast pattern recognition in large amounts of messy, disorganised or heterogeneous data (all your sensory input: sight, hearing, smell etc.). This capability has served as an inspiration for the developments in machine learning.

We are now ready to answer the question of why our brain is so much more power-efficient than a computer. The spiking nature of the electrical signals in the brain is already an energy-saving mechanism, compared to those in our computers. Also, unlike transistors, synapses do not require power to keep the same value of resistance when they are not being used. But, the most efficient is that in this network of neurons and synapses, processing and memory are located in the same area: the synapse contains the information and the neurons make the computations. This is very different from our computer's architecture.

Hardware

Currently, machine learning is performed on computers based on transistors, just as in AlphaGo. In such a computer, the two key components are the processor (CPU) and the memory. The processor performs the computations while it takes and stores the information from/in the memory. In this process currents flow through wires in between the two components, which leads to power dissipation (see Figure 3) and is why your computer needs cooling. Also, the building blocks, transistors, of the processor constantly require power to operate and are designed more for speed and reliability than for energy efficiency. To improve on this, we need to look for different architectures and devices and the brain seems to be a pretty good model for this.

To make hardware that mimics the operation of the biological brain, we should look for analogs of the neuron and the synapse. A neuron-like device can be built out of a few transistors (which is okay for now). Mimicking a synapse, however, is more difficult: it requires many transistors and, therefore, a lot of power.

Instead of using transistors, one could use so-called memristors to mimic a synapse. A memristor is a device in which the resistance depends on the history of the voltage applied to it. In addition, when the device is turned off, the resistance doesn't change and will be the same the next time the device is used (non-volatility). Some types of memristors can have a resistance that is not limited to either 0 (high resistance) or 1 (low resistance) but are able to vary between multiple values in between. This property could allow for STDP, where this resistance should change as a result of the signals of two adjacent neurons. Every time the conditions are met, the resistance should change a little bit. To build a synapse, only a single memristor would be required!

In recent years, research on materials with memristive properties has gained much interest due to these promises of energy efficient non-volatile memory and neuromorphic applications. One example of such a system is shown in Figure 5 where an insulating ferroelectric layer of crystalline $BiFeO_3$ is implemented. A ferroelectric material has an electric polarisation that can be switched, for example by applying a strong enough electric field. This layer is placed on a conducting

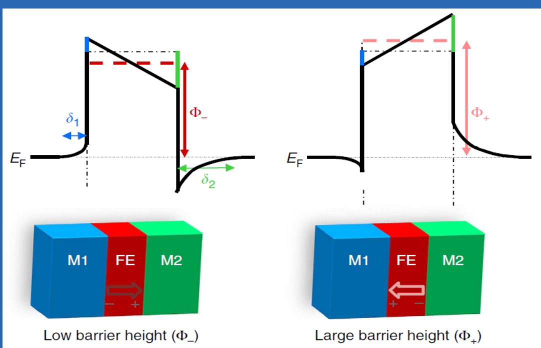


FIGURE 4: Ferroelectric polarisation in relation with tunneling [4]

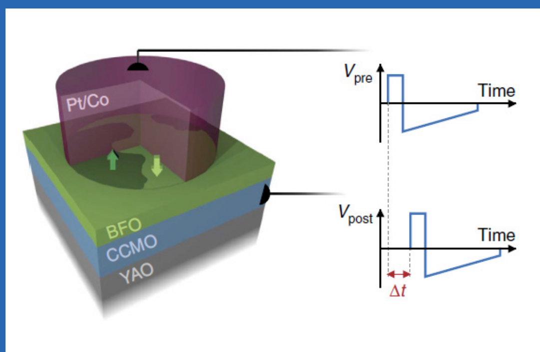
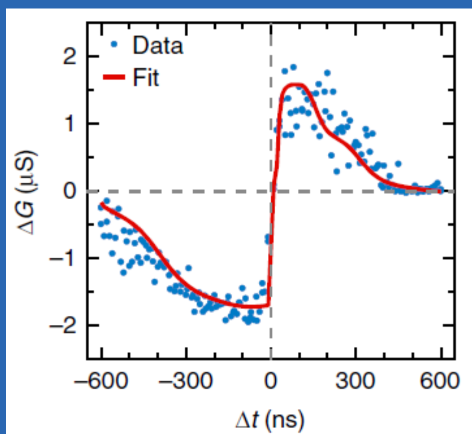


FIGURE 5: Ferroelectric synaptic device (above) and its STDP behaviour (below) [3]



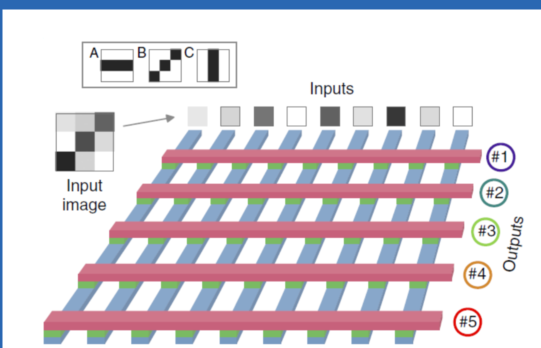


FIGURE 6: Crossbar array with input neurons (top), output neurons (right) and synapses (at the intersections). Every input neuron is connected to 5 output neurons [2]

substrate and on top metallic contacts are placed. At the interface of the insulating $BiFeO_3$ and the metallic contacts, the electronic bands bend due to the internal field created by the ferroelectric layer (see Figure 4). How and how strong these bands are bent depends on the magnitude and direction of the polarisation in the ferroelectric material. For a very thin layer of $BiFeO_3$, tunneling conduction can occur through the insulating barrier. The rate of tunneling depends on the bending of the bands and therefore on the direction of the polarisation. Switching the ferroelectric material, thus, changes the resistance of the device.

In reality the film is not perfectly homogeneous. Therefore, the ferroelectric does not switch everywhere at the same electric field strength and one can use this to manipulate the change in resistance: a multi-value memristor is born. In Figure 5 the result of an STDP experiment of such a device is shown. Here the same behavior is observed as in a biological synapse.

One can design cross-bar arrays of these devices as in Figure 6. The lines resemble the dendrites and axons of the neurons, while the synapses are at the nodes connecting them. Such networks can then be trained for learning in a similar way as neural network algorithms are trained.

Utilising as-grown networks

This was only one example; there are many approaches out there, utilising magnetism, spintronics, electro-chemistry, phase change materials and many more – ideas are popping up everywhere. But the brain has even more to offer. Industry tries to make everything ordered and well-controlled, as in the cross-bar arrays. However, reaching the 10^{15} synapses in a reasonable volume seems unattainable with current top-down processing techniques. In addition, our brain is more like a spaghetti of neurons. Apparently a more chaotic arrangement of devices can also work fine, or maybe even better. In our lab in the Nanostructures of Functional Oxides group we investigate the idea of using dense, self-organised networks of such materials instead (see Figure 8). The hope is that this will allow for the study of dynamical behavior of networks of larger amounts of nodes and perform a statistically relevant analysis that can determine if or under which conditions the different types of memristive materials can learn•

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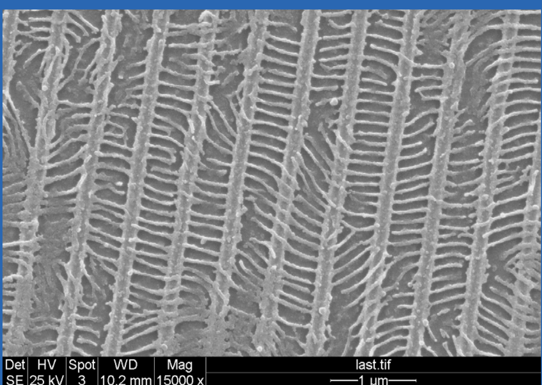

FIGURE 7: SEM image of a self-organised network of an oxide using polymer templating (courtesy of J. Xu, Macromolecular Chemistry and New Polymeric Materials group)

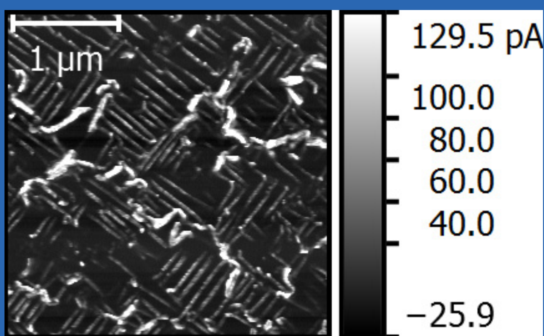

FIGURE 8: Conductive AFM image of self-organised conducting domain wall network in ferroelectric BiFeO3 (own work, Nanostructures of Functional Oxides group)

A Mechanical Design to Unearth the Origin of the Universe

AUTHORS: DR. C.RIGOLLET, ING. M.F. LINDEMULDER, ING. H.A.J. SMIT, PROF. DR. N. KALANTAR-NAYESTANAKI

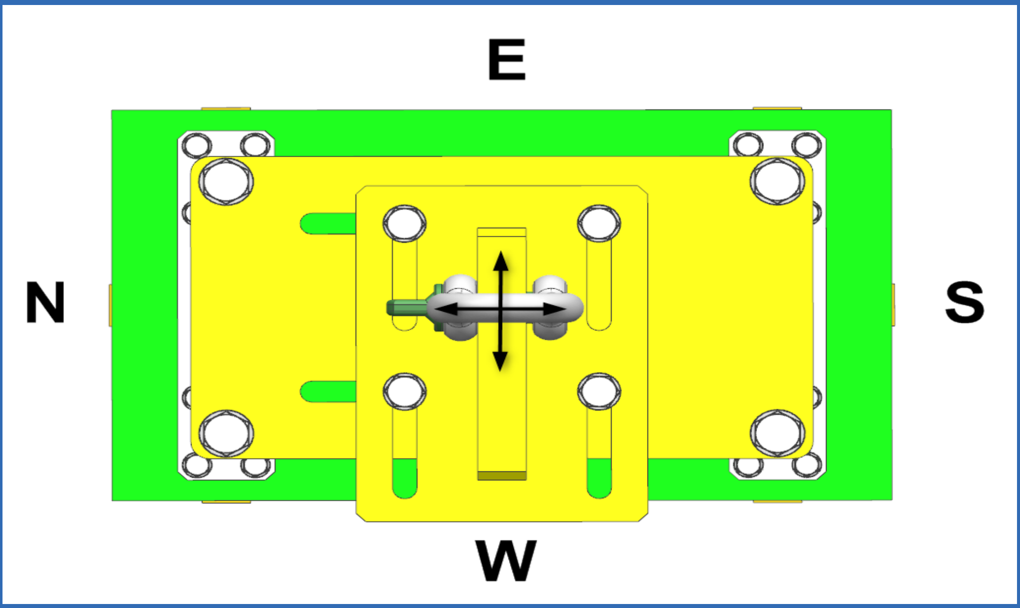

FIGURE 3: Top plate of the plug showing the possible lateral movements in East-West and North-South directions, resulting in a tilt of the plug

Everyone knows that the answer to the ultimate question of life, the universe and everything is 42 [1]. But can we really reduce the origin of the universe to such a random number? The real answer lies above our heads and underneath our feet, in the stars and in the earth, in the elements that make up everything. FAIR, an upcoming large-scale accelerator facility for heavy ions, will give scientists from all over the world an opportunity to solve the giant puzzle of the origin of the universe, one little piece at a time.

FAIR is the successor of GSI Helmholtzzentrum für Schwerionenforschung in Darmstadt, Germany, and will provide beams of antiprotons and very exotic ions to discover unknown states of matter and study the evolution of the universe. The production and guiding of the particles to the experimental areas are complex and require many disciplines working in synergy to achieve this technical feat. Like most things in life, the realisation of an idea or a concept starts with a design, and in the case of the Super FRagment Separator (Super-FRS) at FAIR, a mechanical design.

KVI-CART, in close collaboration with GSI, is heavily involved in the design and manufacturing of some critical elements of the Super-FRS, where secondary exotic beams are created, selected and directed to different nuclear and atomic physics experiments. The target station is the most significant and intricate part of the Super-FRS, as it is the place where the radioactive species are born. The target, on which the primary ions impinge, is a rotating wheel made out of graphite and is housed in a large vacuum chamber, along with several beam diagnostic components. The tremendous amount of radiation generated at the target needs to be absorbed in shielding material to reduce the activation on the upper side of the chamber and allow human intervention. Therefore, every element in the target station is connected to the bottom of a so-called shielding plug, which can be inserted or removed from the vacuum chamber remotely.

The mechanical design of the vacuum chamber must fulfill strict conditions regarding dimensions and tolerances as it has to be integrated into the surrounding iron radiation shielding of the Super-FRS. For instance, the bending of the chamber under its weight or by air pressure must not alter its function or shift the plugs by more than 0.2 mm with respect to the aligned positions. The chamber has five inserts and the devices mounted on the plugs have vertical drives to move and remove the various beam diagnostic detectors, the target wheel, target ladder and collimator from the beam axis. Figure 1 shows a cross section of the target chamber with the plugs inserted.

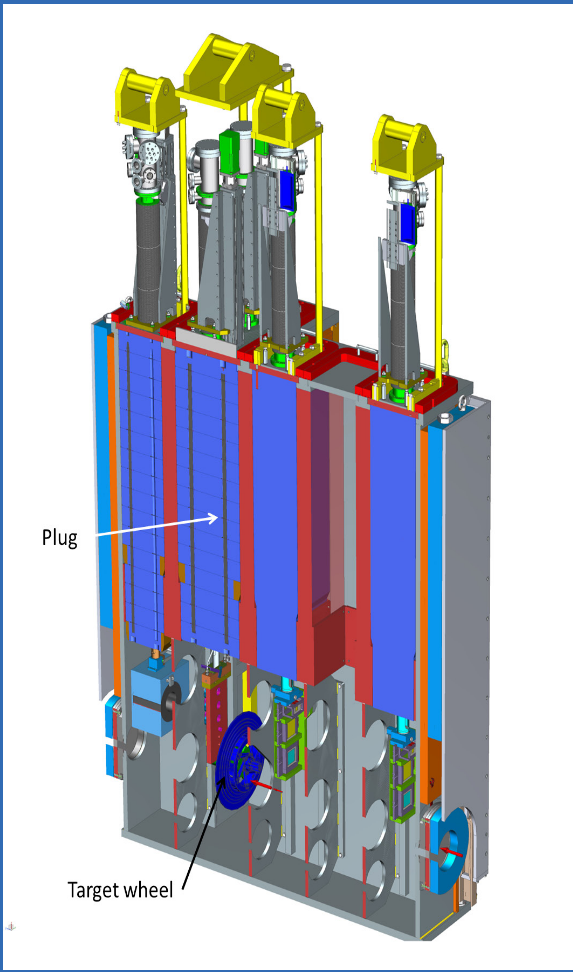

FIGURE 1: Cross-section of the target station.

The height of the plugs is 2200 mm, which includes at least 1500 mm of iron shielding to satisfy radiation protection guidelines. Situated in the high radiation area of the Super-FRS, the target station components need to be handled remotely with a robot. This implies lifting the plugs and transporting them to a hot cell, where parts can be replaced or exchanged. The plugs can then be reinserted in the chamber. Weighing at more than 4000 kg, the accuracy of the positioning and guiding of the plugs during insertion is a crucial part for remote handling. Therefore, a real-size dummy plug was manufactured and a test setup mimicking the vacuum chamber erected to verify the guiding structure of the plug into the chamber and determine the limits of displacement and tilting of the plug with respect to the vertical still allowing a safe insertion.

The dummy plug is made out of blocks of stainless steel stacked one millimeter apart to avoid having air trapped in the chamber and achieve a better vacuum. The structural integrity of the plug is realised by the addition of four rods passing through the whole length of the dummy. Four legs with tapered ends are connected to the bottom block and provide the guiding system into an insert of the chamber.

A frame of UNP steel profiles was manufactured to simulate the shape of an insert, with plates of stainless steel connected to the inside of the assembly to ensure a smooth gliding of the plug into the enclosure and reproduce the real-life situation in the target chamber. A normal crane hook was used to lift and lower the plug into the U-frame. The setup is shown in figure 2. The first step in testing the proper functioning of such large and heavy contraption is to assess the reproducibility of the movement in and out of the structure. Measurements of the space between the legs and the structure are taken on the four sides at two corners each time the plug is lowered. The largest deviation observed is 50 μm. After a series of lifting and lowering the plug, the blocks are visually inspected for damages that could affect the functionality of the system.

The limit of lateral displacement is obtained by moving the crane. The maximum displacement observed for which the plug can still be lowered in the insert is 65 mm. This value largely exceeds the required one of 20 mm. The tilt of the plug can be achieved by altering the position of the lifting point of the plug, as can be seen on figure 3. Several combinations of displacements were tested and the limit was found at 28 mrad, again surpassing the requisite value of 5.7 mrad.

The successful plug test is a first step towards the construction of the target station and the completion of the Super-FRS at FAIR. Without (mechanical) engineering, the greatest scientific ideas would stay just that, the theories left unverified, the universe still a mystery. "We are stardust, we are golden, we are billion year old carbon", and we can prove it•

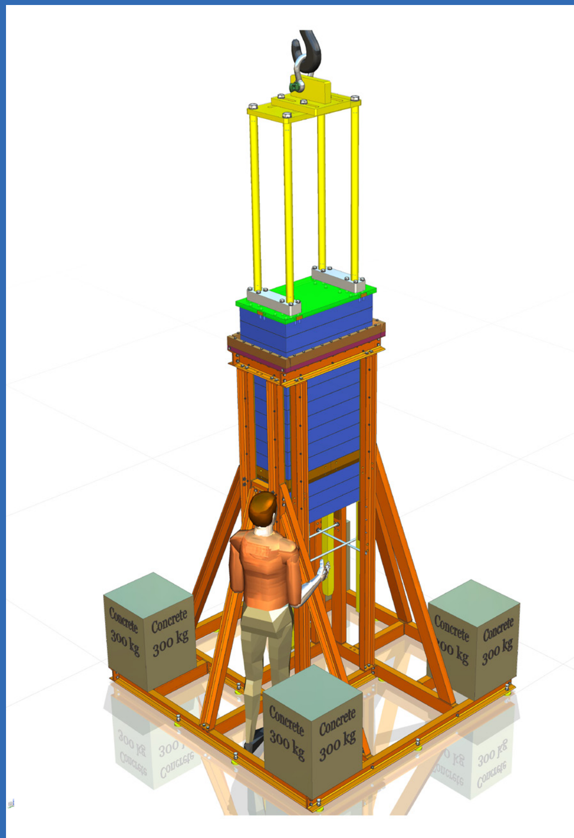

FIGURE 2: Test setup with plug hanging from a crane hook

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The Muon Problem

AUTHOR: JONAH STALKNECHT

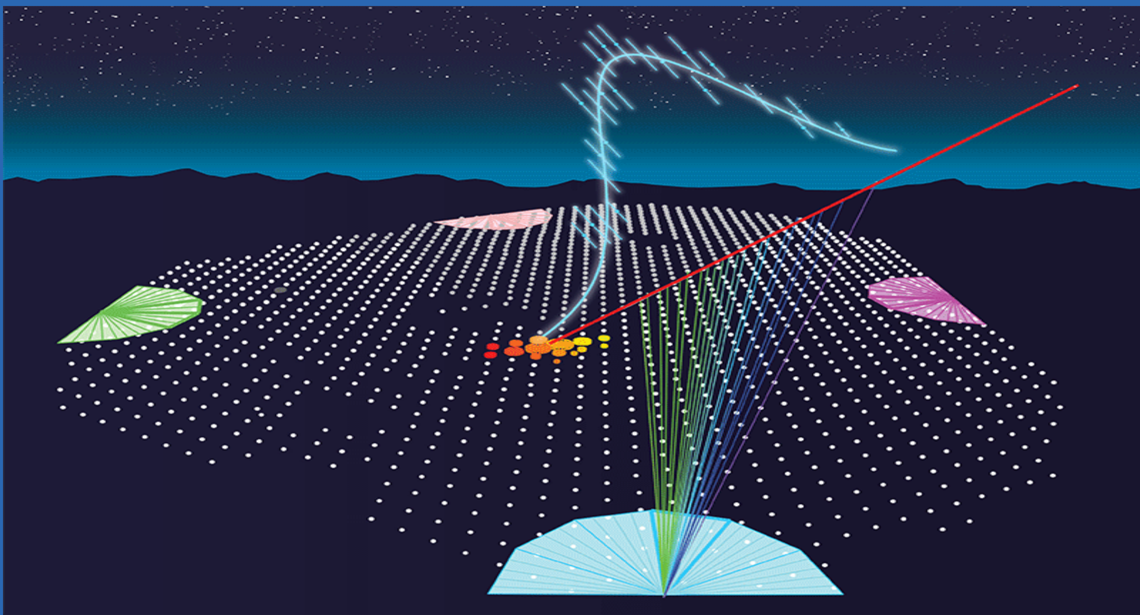


FIGURE 1: A schematic picture of the Pierre Auger Observatory in Argentina. The red line represents an incoming cosmic ray. The white dots and coloured semicircles are different types of observatories.

Cosmic rays can attain energies up to a million times higher than the energies reached at the LHC. When these cosmic rays collide with particles in the atmosphere this enormous amount of energy will create many new particles. Why and how this happens is understood quite well, but our predictions do not match the data. 30-80% more muons seem to be created in the air shower following the initial collision with the atmosphere than our models predict.

Cosmic rays reach the earth's atmosphere all the time, the lower energy particles (~10^{10} eV) reach the earth more than once per second per square meter. When considering the muon problem, we are mainly interested in the so-called "Ultra High Energy Cosmic Rays" (UHECR) which have energies greater than 10^{18} eV (compare this to energies at LHC, where particles reach about 10^{13} eV). These are a lot rarer, they reach the earth about once per square kilometer per year. The exact origin of these UHECRs is still a topic of debate to this day.

When one of these particles interacts with the atmosphere it will produce many more energetic particles which will either decay, or it will collide again with a particle in the atmosphere where it will once again create a bunch of more particles. These newly created particles will undergo the same process. Every time a particle collides to create more particles we call it a new generation, the entirity of the particles created is called the air shower. At some point the energy of the particles is so low that more particles are being stopped than created, this point is called the shower maximum.

We have very sophisticated models to simulate these air showers. And as good as these models are, they all fail to correctly predict the number of muons created. In 2015 the Pierre Auger Observatory, a 3000 km^2

large observatory in Argentina, observed 30-80% more muons than our models predict (the 30-80% range is dependent on what model you compare the data to). This is what we call the 'muon problem'.

Every adjustment you make to your model to resolve this muon problem has to have two things: it has to increase the amount of muons N_μ (obviously), and it has to not change the depth at which the shower maximum occurs, X_{max}, too much. This last one has proven to be quite tricky, simple attempts to resolve the muon problem (like decreasing the amount of generations in the air shower) fail here. Because the energies involved are so high, there is a lot of freedom to come up with new physical ideas; the creation of miniature black holes, exotic particles or supersymmetric particles have all been proposed, but they all fail to predict the right X_{max}.

Luckily not all theories strike out at this, some theories seem to be able to work. Most theories that have as a main consequence that less pions will be created will not alter X_{max} too much, while still being able to influence the number of muons that are created.

One of the simpler possible solutions is that particles that are created have a higher chance of being in an excited state. Another artifically increases the number of baryons that are created in the aftermath of the collisions. There are also more complex solutions based largely on new physics, such as the restoration of chiral symmetry at these high energy densities, or a percolation of color strings created between the partons of interacting particles.

To find out which (if any) of the proposed solutions is correct, we look at the way X_{max} and N_μ depend on one another, as this can greatly differ for any of the proposed solutions. To find out what $X_{max} - N_\mu$ dependency we see in nature we will have to wait for more observations. For example by Auger Prime, an improvement on the Pierre Auger Observatory, expected to run until 2024. Auger Prime is expected to deliver a data set twice the size of what we currently have with improved accuracy for the muonic energy fraction of the air shower•

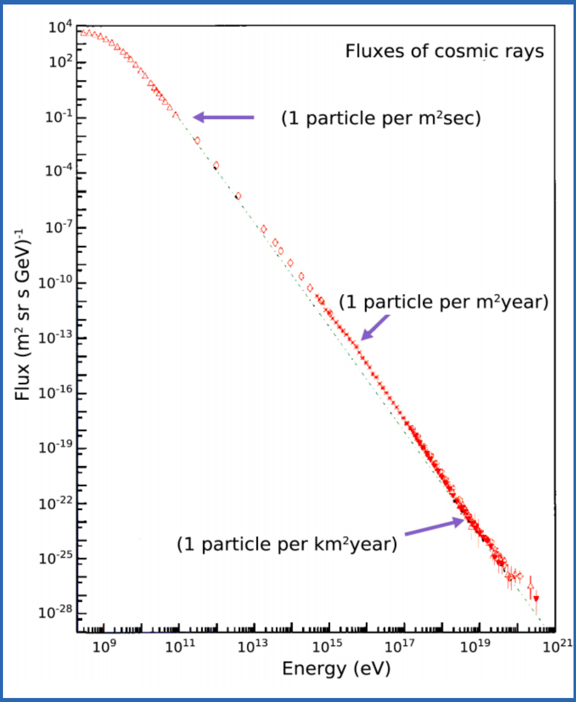


FIGURE 2: The flux of cosmic rays that reach the earth.

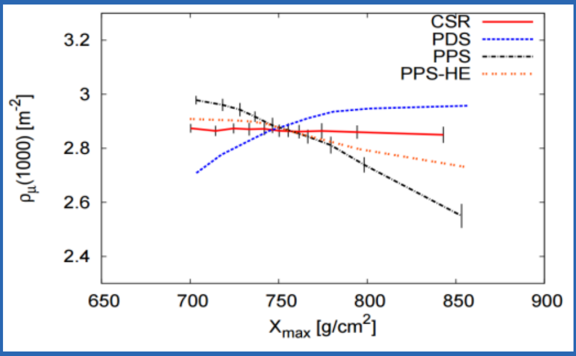


FIGURE 3: The ρ_μ — X_{max} dependency for 4 different proposed models. ρ_μ here is the muon density and can be compared to the N_μ the text.

Brainwork: Symbolic Square

AUTHORS: **JOHAN JAGER** AND **HELENA JAGER**

Due to an editorial mistake, last issue's puzzle was incorrectly displayed, rendering it unsolvable. The board of editors apologises for the inconvenience, and thanks the people who pointed out the mistake. This is the correct version, enjoy!

Each square is either TRUE or FALSE. If a square is true, then all statements in that square are true. Similarly, if a square is false, all statements in that square are false. Each square has exactly one symbol. (Either κ, λ, π or τ). These symbols can help you identify properties of the square. Your task is to find out for all squares whether they are TRUE or FALSE and which symbol they have. Adjacent squares include diagonals.

all squares in this column are FALSE. There is at least 1 TRUE corner square.	The square directly to the right has a τ or π symbol. The bottom row has more squares with κ symbols than squares with λ symbols.	The difference between the total number of π symbols and κ symbols is exactly 1. There is no square with a κ symbol that is adjacent to 3 or more squares with a λ symbol.	This square has a π symbol.	This Square has no π symbol. The square directly below has a τ or π symbol.
This square has a λ symbol.	This square is adjacent to at least 1 square with a τ symbol. Directly to the right of each square with a λ symbol must be a TRUE square.	There is at least 1 κ symbol in the bottom row. This square has a κ symbol.	Squares directly to the right and left have the same symbol. The square directly below has a π symbol.	There is exactly 1 π symbol in the bottom row.
Every square adjacent to a square with a π symbol and a square with a λ symbol is TRUE. This square has a π or κ symbol.	There are exactly 6 adjacent TRUE squares.	There is no λ symbol is this row.	Squares directly to the right and left are TRUE.	There is no κ symbol in this row.
This square has a λ symbol.	The square directly above has a τ symbol. Every column has at least 1 TRUE statement.	There are exactly 7 squares with τ symbols.	The square directly to the left has no λ symbol. The square directly below has a λ symbol.	Every column has exactly 2 π symbols.
This square has a τ symbol. There is a column that contains 3 or more squares with the same symbol.	There is a column with exactly 2 FALSE squares. There is exactly 1 square with a λ symbol in this column.	This square has a λ or κ symbyol. The square directly above is FALSE.	Adjacent to each square with a τ symbol is at least 1 square with a τ symbol.	All squares with a τ symbol have the same truth value.
Some corner squares share the same symbol. This column has all 4 symbols.	Each row has at least 3 different symbols.	Every square with a κ symbol is adjacent to at least 1 FALSE square.	Every column has exactly 2 κ symbols	There is a square with a τ symbol in this row

Winter Soup: Snert

AUTHOR: RICK

As internationalisation can go both ways, we have a recipe for a typical Dutch dish this time. When winter starts, my grandma always makes some nice snert, which is great for when it's cold outside. Here's a recipe.

2 liters of water
1 tablespoon salt
400 grams of split peas
2 chuck cutlets (~250 grams)
1 bay leaf
1/2 celeriac
1 onion
250 grams of leeks
25 grams of celery
100 grams bacon
1 rookworst

As the snert can easily burn on the bottom of the pan, always stir regularly while the soup boils/simmers!

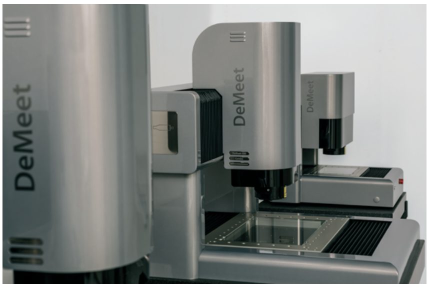
Put the water, toghether with the salt, split peas, cutlets, bay leaf and peeled celeriac, cut in cubes, in a pan, bring it to a boil, and let it simmer for 30 minutes. During this time, cut off the green leaves and the bottom of the leeks, and cut the remaining parts into medium-sized rings. Also cut up the onion and celery.

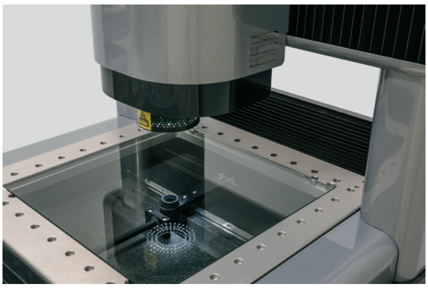
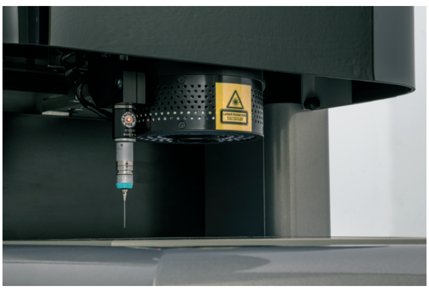
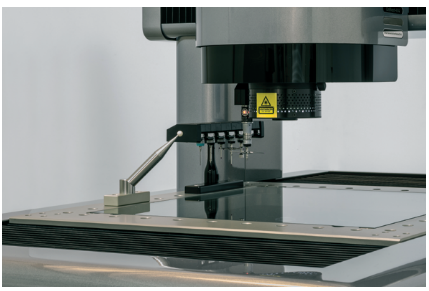
Take the cutlets out of the pan and cut it into cubes after removing the bone. Put the cutlets, celery, onion and leeks into the soup, stir and let it simmer again for 10 minutes. Now put the bacon and rookworst in the pan, and let it simmer for a final 10 minutes. When this is finished, take the rookworst out of the pan, cut it into pieces, and put it back into the soup.

The soup is finished, eet smakelijk!

Legend goes: to make the soup tastier, keep it in the fridge for a day, then reheat it.

FIGURE 1: It's tastier than the picture makes it look.



Schut Geometrische Meettechniek is een internationale organisatie met vijf vestigingen in Europa en de hoofdvestiging in Groningen. Het bedrijf is ISO 9001 gecertificeerd en gespecialiseerd in de ontwikkeling, productie, verkoop en service van precisie meetinstrumenten en -systemen.

Aangezien we onze activiteiten uitbreiden, zijn we continu op zoek naar enthousiaste medewerkers om ons team te versterken. Als jij wilt werken in een bedrijf dat mensen met ideeën en initiatief waardeert, dan is Schut Geometrische Meettechniek de plaats. De bedrijfsstructuur is overzichtelijk en de sfeer is informeel met een "no nonsense" karakter.

Op onze afdelingen voor de technische verkoop, software support en ontwikkeling van onze 3D meetmachines werken mensen met een academische achtergrond. Hierbij gaat het om functies zoals ***Sales Engineer***, ***Software Support Engineer***, ***Software Developer (C++)***, ***Electronics Developer*** en ***Mechanical Engineer***.

Je bent bij ons van harte welkom voor een oriënterend gesprek of een open sollicitatiegesprek of overleg over de mogelijkheden van een **stage-** of **afstudeerproject**. Wij raken graag in contact met gemotiveerde en talentvolle studenten.

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