arj7192@gmail.com

ASHISH JHA

ch.linkedin.com/in/ashishri bitbucket.org/arj7192 github.com/arj7192

WORK EXPERIENCE

Senior Data Scientist Tractable Oct 2018 – Present

Building Car Insurance Claims Fraud Detection AI Pipeline. Tabular Claims Data + Multi Task DNN Model (PyTorch)

Senior Data Scientist Sentiance May 2016 – Aug 2018

- Leading the major data science team of 4 data scientists and 2 data engineers working on mobile sensor data.
- Constructing an xgboost + LSTM framework (in keras) for GPS based transport mode classification.
- Implemented a user timeline event predictor using deep learning CNN + LSTM (on tensorflow).
- Created data science tools using (i) spark (for spark jobs) (ii) boto3 (for AWS), (iii) javascript (for labelling data).
- Developed smart home AI based solutions for Philips Vue and Samsung SmartThings Hub.

Internship + Master Thesis

Sony Deutschland GmbH

Aug 2015 - Feb 2016

Implemented a CNN based audio event detection model with Theano on the UrbanSound dataset.

Applications Engineer

Oracle India Pvt Ltd

Jun 2013 - Aug 2014

- · Developed APIs for Social Customer Service project that were included in Oracle RightNow 14.8 product release
- Created a system-startup shell script for my team that builds the trunk, database and runs the unit-tests daily

EDUCATION

Lausanne, Switzerland

École Polytechnique Fédérale de Lausanne

Sep 2014 – Feb 2016

- M.S. in Computer Science, GPA: 5.67/6.0 (ECTS)
- Coursework: Pattern Classification and Machine Learning; Big Data; Computer Vision; Natural Language Processing; Distributed Algorithms; Distributed Information Systems; Advanced Computer Graphics

Roorkee, India

Indian Institute of Technology, Roorkee

Jul 2009 - May 2013

- B.Tech. in Electrical Engineering, CGPA: 9.14/10.0
- Coursework: Digital Image Processing; Data Structures; Programming with C++;

PROJECTS

- Human pose estimation using Deep Learning [EPFL] (2015). Used RGB images from Human80K dataset to regress 3D poses using deep convolutional neural network. Obtained state-of-the-art results. Theano, Matlab.
- Deep Learning to identify patterns in Manuscripts [EPFL] (2015). Implemented image pre-processing task for manuscript pages and extraction of words and sentences from handwritten text. OpenCV-Java, Spark.
- Travel Search Optimizer [Self] (2015 present). Finding when-to-search for best availability and prices at sites like blablacar by learning the variation patterns using neural networks. Scikit-Learn, TensorFlow, Amazon EC2.
- Implicit feedback based Recommender System [EPFL] (2014). Built a song recommender system based on user-user collaborative filtering using alternating least-squares model. Matlab.
- Person detection in Images [EPFL] (2014). Designed an SVM and a logistic regression model using HOG (Histogram of Gradients) of images as input features. Evaluated using ROC curve. Matlab

LANGUAGES AND TECHNOLOGIES

- Python (sklearn, tensorflow, keras, pandas, jupyter, flask, seaborn); C++/C; SQL; D3js; HTML; Javascript
- AWS (EC2, S3, EBS, EFS, AMI,..); Spark; Docker; Kafka; Linux; Git; PyCharm; Datadog; Jira; Confluence

ADDITIONAL EXPERIENCE AND AWARDS

- Second Prize, IBM Technology Contest 2011: For: 'Using Wearable Technology Against Rape in India'
- World finalists, Thought For Food, Berlin, 2013. Ambassador, Thought For Food, Europe, (2017-now)
- Coursera courses: Mining Massive Datasets, Machine Learning, Deep Learning, Algorithms

ANTLER INNOVATION UK LIMITED

Company No: 11707590

145, City Road, London, England, EC1V 1AZ

April 23, 2019 London, UK

Letter of Recommendation

For the attention of Tech Nation:

Regarding the application of Mr Ashish Ranjan Jha for Exceptional Talent status in the UK in the field of digital technology.

Ashish Ranjan Jha has been accepted on Antler's start-up program in London, starting in June, 10 2019.

Antler (www.antler.co) is a global start-up generator and early-stage VC that is building the next big wave of tech. With the mission to turn exceptional individuals into great founders, Antler aims to create hundreds of companies globally over the next five years. We select the world's most brilliant and determined people, help them find the right co-founder(s) and connect them to a top tier network of advisors and experts worldwide. Antler breaks the barriers to entrepreneurship by providing funding from day one and building strong teams from the ground up, while enabling our founders to rapidly launch and scale their ideas.

Our program is a unique opportunity for someone like Ashish Ranjan Jha to build an innovative and impactful business in the UK, and it is exactly people like him that allows to run our business model. Ashish Ranjan Jha is an exceptional talent that has been at the forefront of Data Science. Having 5+ years of experience in the tech sector and more recently a Senior Data Scientist— Tractable, Sentiance & Sony— he has helped them scale to millions of uses and has been instrumental in setting up Car insurance claims fraud detection by building an Al pipeline in Tractable. Over his career he has hired, mentored and managed teams to deliver exceptional results.

In summary, Ashish Ranjan Jha brings experience as a business head of having set up teams, scale up products and regional expansion from scratch, has the subject matter expertise in mobility and urban sector built through constant learning and education, and has been an exceptional leader in furthering the cause of innovative technologies in those sectors by being a spokesperson for mobility, telematics and urban innovation at large.

We highly recommend Ashish Ranjan Jha for Exceptional Talent status in the UK.

If any further clarifications are needed, I can be reached at:

Email: @antler.co

Phone:

https://www.linkedin.com/in/la

Antler Innovation UK Limited

Kvaalen Partner Date: 26-04-2019

For the attention of Tech Nation:

Regarding the application of Mr Ashish Ranjan Jha for Exceptional Talent / Exceptional Promise status in the UK in the field of digital technology.

I, have come to know the applicant since May 2016 in the capacity of data scientist.

As an emerging start-up back in 2016, Sentiance was looking to expand its data science team which at the time consisted of only 3 people. As chief data scientist at that moment, I was tasked to bring in a top talent that could help us build out a world class team

After a thorough recruitment procedure consisting of several technical tests and interviews, Ashish emerged as our top candidate out of a pool of 12 eligible candidates that were carefully selected from 180 applications. His theoretical knowledge and understanding of the field of artificial intelligence was perplexing and since then, no other candidate ever scored as high on our standardized technical tests.

Ashish was hired as machine learning expert in our data science team, and proved an invaluable coach and leader as our team grew from 3 people to 15 people over the course of that year.

During his first year at Sentiance, Ashish researched, implemented and productionized a state-of-the-art behavioral prediction algorithm based on recurrent neural networks. At a time where deep learning was still in its infancy, this contribution quickly became a USP for Sentiance, and continues to do so today, directly generating a significant portion of Sentiance's recurring revenue.

Apart from his incredible technical capabilities, Ashish quickly proved to be a talented leader as he took the lead on a big smart-home project in the IOT space together with Samsung, our main investor at that time. Ashish successfully balanced client communication with steering and coaching a team of junior data scientists and engineers with delivering state-of-the-art results in a timely and professional manner.

To capitalize on this, we decided to promote Ashish to senior data scientist after which he became responsible for hiring and coaching new Al researchers on the one hand, and for heading up our Al research team, called 'Future Years', on the other hand.

As Chief Innovation officer, I can honestly state that the combination of deep technical knowledge and leadership skills I found in Ashish, is extremely rare to find. Sentiance grew from 8 people in 1 office to 70 people with offices in 6 different countries during the time Ashish was with us.

Given his talent, Ashish has ample opportunities when it comes to the job market. However, it would be a waste to not apply that talent either at a state-of-the-art Al company like Facebook or Google, or at a newly founded start-up company where he could change the world for the better. In both cases, moving to London or the UK in general would be any Al researcher's first choice.

It is only through people like Ashish that innovation can truly take place, and any company or even country would be enriched immediately if it were able to attract this kind of talent.



Concretely, I strongly believe Ashish will directly impact the UK digital economy if he were given the chance to start a new high tech company and grow it like he grew Sentiance, from start-up to internationally recognized Al scale-up in only a few years time.

If you have any questions concerning the information contained in this letter, please contact me directly.

Sincerely,

@sentiance.com

Phone:

LinkedIn: https://www.linkedin.com/in/v

Resume: Attached



Mr Ashish Jha

| PAID BY Tractable Ltd | |
|--------------------------|--|
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| | |

| EMPLOYMENT DETAILS | |
|--------------------|--|
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Pay Period: 01/02/2019 - 28/02/2019 (Tax Month 11)



Mr Ashish Jha

| PAID BY Tractable Ltd | |
|--------------------------|--|
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| EMPLOYMENT DETAILS | |
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Pay Period: 01/03/2019 - 31/03/2019 (Tax Month 12)

| SERVICE AGREEMENT | | | 2. |
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| DAT | ED | 21 June 2018 | 2.1 |
| PAR | ries | | 2.2 |
| (1) | TRACTABLE LTD. | | 2.2 |
| (2) | Ashish Ranjan Jha (the "Executive"). Ashish Ranjan Jha | | 2.3 |
| OPE | RATIVE PROVISIONS | | |
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IN WITNESS whereof a duly authorised representative of the Company has executed this agreement and the Executive has executed this agreement as his Deed on the date of this agreement.

Signed and delivered by the said

ASHISH RANJAN JHA as his deed in the presence of:

Signed by behalf of Tractable Ltd.

) Jun 26, 2018

4.5



Sony Deutschland GmbH Stuttgart Technology Center

Mr Ashish Ranjan Jha

07.05.2015

Masters thesis

Dear Mr. Jha,

As already mentioned in my email please find enclosed your employment contract, the employee questionnaire and the checklist.

Please sign one version of the contract, complete the empoyee questionnaire and return both to me as well as the documents you have already by hand.

We are looking forward to welcoming you in Sony. Please contact me if you have any quesitons or inquiries.

Best regards,

Sony Deutschland GmbH Human Resource Services







Sony Deutschland GmbH Stuttgart Technology Cente

STUDENT CONTRACT for preparation of his MASTER THESIS

Between

Sony Deutschland GmbH Stuttgart Technology Center

(named hereinafter 'Sony')

and

Mr residing at Ashish Ranjan Jha

(named hereinafter 'student')

1. Type of thesis

1. Type of thesis

The student, according to the provisional subject of the Master Thesis:

"Context representation and classification ",

The contract is based on a valid residence permit which allows the student to write his thesis in Germany.

2. Duration of the thesis work

SONY

SONY

| | 9. Confidentiality | |
|------------------------|---|--|
| 3. Probationary period | | |
| 4. Payment | | |
| 5. Working hours | 10.Final Provisions | |
| 6. Vacation | | |
| 7. Thesis | Stuttgart, this 30.04.2015, this Sony Deutschland GmbH i. V. i. V. | |
| 8. Other agreements | Ashish Ranjan Jha | |
| | | |

Predictive superpowers: Applying deep learning on mobile sensor data to predict human behavior - Sentiance

PURCORN SOUTHING CONFUNY DOCS CONSICT

By Ashido Jose April 25, 207

Predictive superpowers: Applying deep learning on mobile sensor data to predict human behavior

ARRIGA NEWSENCE DATA SCENCE

At Sentiance we believe that enact devices, applications and the Internet of Things should work on your behalf, conforming your desires and presently your needs. Who all tithe Internet of You. We are building the Internet of You, by analyding sensor data to recognize behalf only the Internet of You, by analyding sensor data to recognize behalf only of the Internet of You, by analyding sensor data to recognize behalf or of the Internet of You, by analyding sensor data to recognize

Our mission is to enable companies not only to be contest aware and deliver timely and highly personalized experiences (serve 5 respond) last data to be an estep alread and proactively provide nelevant recommendations by predicting content and preventing needs (predicts 6 engage).

By lower gifty smortphone somer data such as associatements gyrassops and boards in himmalian, we distinct a person's context on affected best which we call the 6 Visi of context. Who White Miller Whotion Why Although boards in (White) and activity detected (What) availables are during the targeting without it owing the user's complete context including the intent and personality profile, your message requigibility but releases.

Where is the person coming from and where is he going? Knowing the before and after trip activities adds highly relevant contestual insights.

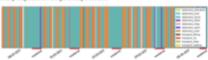
So, predictive analytics is a big thing to us. Our aim is to analyze behavioral patterns based on realtime sersor data and build predictive models that our foresee the future.

PREDICTING A SERIES OF EVENTS TO EXPLAIN INTENT

The input to our prediction model is an event time in eauch as:



The figure below flustrates a simple vention of a real user's timeline with a very regular lifestyle that serves as input to the prediction model. Note that daily aren'verk commisses and weekend periods and deadly recognised at Art Act and the model of the cose.



To foresee not only what a person will be doing, but also why he will be doing it, we need to be able to predict several events ahead. Consider the fall owing example:

₩ NOW > A PREDICTED

in order to explain the intent of the predicted 'our' event, our modelineeds to be able to understand what is likely to happen further in the future. For example:

** NOW > A PREDICTED > A PREDICTED

Based on the current and future-worth, we can now softing assurer that the underlying intent of the predicted is of event of it in further incrementate work? So predicting further of what in time allows us to assign meaning to both current and great-dated worths. These semantics we what we call more than examples of which are "shapping routine", 'commutate work', 'bildwendrop-off', 'business tipi', hidding,' and more "shapping routine", 'commutate work', 'bildwendrop-off', 'business tipi', hidding,' and more "shapping routine", 'commutate work', 'bildwendrop-off', 'business tipi', hidding,' and more "shapping routine", 'commutate work', 'bildwendrop-off', 'business tipi', hidding,' and more "shapping routine", 'commutate work', 'bildwendrop-off', 'business tipi', hidding,' and more "shapping routine", 'commutate work', 'bildwendrop-off', 'business tipi', hidding,' and more "shapping routine", 'commutate work', 'bildwendrop-off', 'business', 'b

Our first attempt to solve the prediction problemballed down to a simple Markov Chain like approach where we madeled a sequence of events as:

 $p(x_1,...,x_n) = p(x_1)p(x_2|x_1)...p(x_n|x_{n-1})$

The problem with this approach however, is that it is limited by the Markov assumption stating that the conditional probability distribution of future states only depends on the current state. As a result, this

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Thus, the network fails to learn that a person that arrives at work by bliss, is also likely to leave work by bliss in the wentry. It awaits this kind of behavior, we weak! I like to condition our Bellhoods on all past observations, houldcall, madeling the file live lipit motions.

 $p(x_1, ..., x_n) = p(x_1)p(x_2|x_1)p(x_3|x_2, x_1)p(x_4|x_2, x_2, x_1)...p(x_n|x_{n-1}..., x_1)$

Simply increasing the order of the Markov Chain or Bayesian network to achieve this would quickly lead to overfitting, Indiad, we want our model to automatically figure aut which longer-term dependencies matter and which found.

This is where a Long Short-Term Mirmony (LSTM) recurrent neural networks a ame in: A great is idepth explanation of hore LSTM were in its available here. In what, LSTMs allow the neural network to automatically learn which long-term patterns are important to remember, and which are also be frequented autofals.

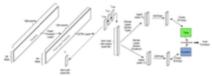
We'trained an LSTM-network to learn to predict both the next-west type, and the duration of the current over. This allows us to determine what the presen inguing to do not, and when this is Buly to happen. By training a striplemated because are severed the assuranced or net-worth cure training, who restouch learns to encode general human behavior, thereby enforcing bemporal conditioning at

More over, using a beam-wanth approach, popular in M.P. related Eterature, we are able to predict complete Maure threline Instead of firstly the next event. By retaining only the topk most likely beams, we and up with everal prediction hypotheses:



MODEL ARCHITECTURE AND TRAINING

The following figure illustrates our model architecture:



The input of the nationals consists of VBI previous events, each of which is represented by a feature vector that a road in the event type $(a_0 - a_0)$ when β , the day of week and time of day, and the duration of the event is 1999 filled events of such a feature vector in 18 batteries the lower.



This feature vector is fed into a dense importing or which basically learns to excede this information into an embedding that one the fell into the LSTM larger that if serves as an excedent After feeding the entire sequence of a events through the larger on a by anne, the final LSTM state encodes both the user's prevent behavior and its most recent events.

The final LSTM state is then fed into a fully connected output layer which transforms the timeline on coding into a representation that is useful for actual of assification.

Two different classifiers are trained simultaneously and end-to-end:

1. Event type classifier (green box): What will the user be doing next?
2. Event duration classifier (bise box): When will the next event start?

The event type softmax autputs 11 probabilities corresponding to the supported autput types:



The overt direction classifier autpain Typothodistics corresponding too bucketed representation of duration. The predicted direction is the sepected duration of the carent event and hence the start time of the met event, while the predicted event type is the espected event type of the next event.

Event durations are bucketed on a log-scale, allowing a fine-grained resolution for short events while a coloner granularity is used for longer events.

Pasing the duration estimation as a described problem instead of a regression problem greatly simplifies the global loss function that combines the duration estimation loss and the event type loss. Cross-entropy is used as the cost for both dissolitions on problems, and the final loss function is defined as the cost field one service.

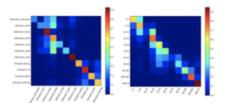
Finally, we perform data augmentation to increase the models generalization capabilities by randomly offsetting event data and end timestamps while selecting mini batches, and by adding random naise to the event durations.

The whole network is trained an term of the userads of read-life timelines from user s with different age, gender, derregraphics and ascie-countrib backgrounds. This of one the network to general is a rad to learn about typical human het-aviac.

RESULTS AND EXAMPLES

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However, note that our ground truth Itself is not labeled manually and thus contains mistales. In fact, manual inspection of the prediction results shows cases where our venue mapping fails to identify a shop ar sport location correctly, while the prediction model did correctly predict the venue type.

Obviously this opens apportunities for future research, where our prediction model might also be useful in a de-noising setting to dean up venue mapping or activity detection errors that happen early on in aur machine learning pipeline.

As a note that the network automatically discovered that transports and venue visits are very different types of events. For example, while 'walking' is sometimes mispredicted as 'cor' - mostly because walking sessions before and other parking the aar are usually very short and are not always picked up by our SDK - the network almost never mis-predicts walking as 'shop' or 'work'.

The duration confusion matrix shows that longer duration, represented by larger buckets, are classified correctly more often than sharter duration. Indeed, walking sessions of up to 10 minutes have quite a large variance and are often predicted to be a few minutes shorter or larger than what is observed.

An interesting observation is that jointly training the network to learn about event tupes and event durations improved the overall accuracy when compared to learning only about event types are vent durations individually. Given the noisy ground truth data when it comes to event types, the event duration labels seems to stabilize the learning process and acts as a regularized

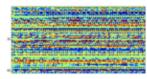
The following video illustrates some prediction results an areal-life timeline:

For better observation of the data, select FULL SCREBN. You can also adjust the speed of the video to your preference.

In the situation above, the network infers that, given the user was at hame, the most likely next events are aar or walking. The right-mast section of the figure, containing two columns represent the different event-types (left) and the softmax-probability associated to them (right). The timeline is placed on the tapmast row in the figure, and is represented as a list of 128 events, each event having a different color,

Below the timeline, are drawn the different internal state and gate values for the LSTM cells, in the form rate panels. Each of the state and gate panels are \$28,64 matrices in the above image, where 128 is the length of the timeline, and 64 is the size of an LSTM cell used in the madel.

Nowlet's zoom into the LSTM States plat:



Among the 64 LSTM cell units (rover of this 128%4 matrix) we can dearly distinguish between (i) those that have learned to depend only on local input features, and (ii) those that have learned to remembe and recagnize temporal patterns in the sequence of inputs. For instance if we take a closer look at row number 61 in the obose motrix

We see that the LSTM cell units simply translate from right to left, almost entirely retaining their state values. This implies that these units have only learnt the features specific to the event they are tied to and have not learnt any temporal potterns, because if they did so, their values would change as the sequence progressed in time. On the other hand, if we look at rewnumber 31 in the same LSTM state

As the units translate from right to left, their value keeps changing in this case and as a whole, there accepts to be smooth variations across the stretch of the entire row-sequence. Two inferences are to be drawn: (i) the smooth variations in the LSTM cell units' state values show signs of acondinations between temporally apresautive cell units, i.e. cell units in a close temporal reighborhood behave similarly which intuitively appears to be an equivalent of a self-learned convolutional lernel (with subsequent max paoling), and (ii) the only way of explaining the variations in LSTM as II unit state values here is that the units do learn temporal patterns apart from the features of the event they are tied to, and that is why they keep changing values as the sequence progresses in time. More interestingly, in the above sample the leftmost units which are more than 100 events back in the past still keep changing their values, which implies that the network is able to learn long term dependencies spanning over 100 events in

Where as rows 61 and 31 are the two extreme cases (of local and temporal patterns respectively), the behavior in the other rows is definitely somewhere in between. The ability to learn long-term dependencies often allows the network to predict event types in cases where even human observers would have difficulty to carrectly predict the correct event.

For example, we noticed cases where the network knew that a user was going to sport at a time at which the user normally does not sport, simply by recagnizing the sequence of events and event dassly manifering the sequence of events and event durations that led up to the aurent manent, the network is able to predict the unexpected. Clearly this kind of behavior can not be accomplished by simple Bayesian approaches modeling $p(event_t|event_{t-1}, time, day)$

PREDICTING FAR AHEAD

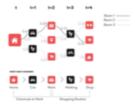
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(e.g. icommute to work or shopping routine), we need to be able to predict several events ahead.

Mareover, we want to predict several hypothesis timelines, such that we can quickly adopt our future predictions if the next event turns out to be different from what we predicted.

hypotheses and retains only those sequences that maximize the total lag likelihood:

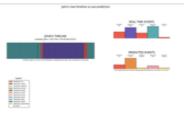


Below is a video that illustrates the beam search based are dictions for a sample user

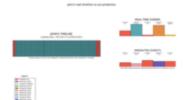
For better observation of the data, select FULL SCREEN. You can also adjust the speed of the video to your preference.

The actual event that happened after Home, was Car, which is among the predictions suggested (i.e. Cor or Walking). Given that the next event was Cox, the model now predicts that the next event is going to be Stationary. Other which as shown below, happens to be a correct prediction.

The above scenario uses real user data and the predictions are made over the Easter-weekend time period. Weekends are usually difficult to predict, but it is evident that in general, the model is close enough at predicting the sequence of future events. It has inherently learnt the meaningful transitions between stationary events and transport events. And has also learnt the duration that a particular eventtype usually spars over (walking means short time, home means long, etc.). However, there is a nario here, which is the Easter Monday (a holiday in Belgium). If we notice at the insta shown below, the model on Sunday night thinks that the next day is a work day, when it actually is not



It makes sense for the model to think so, because after all, an Easter Monday happens rarely enough to be considered an anomaly. However, the good partiz that on the next day, as soon as the user goes to a place which is not his/her workplace, the madel immediately adapts itself to predict further events in the future as if it was not a typical working day, but a weekend-ish day with shapping and other events. This displays the dynamic adaptability that our new prediction madel passesses



Apart from the above weekend example, below is a video showing predictions for a weekday routine where the predictions look more carrect (as expected, because weekdous are more predictable on

For better observation of the data, select FULL SCREEN. You can also adjust the speed of the video to

CONCLUSION

Based on our state of the art machine learning and sensor fusion pipelines part 1 and part 2 Sentiance

Our deep learning based prediction pipeline adds extremely predise predictions to our solution. allowing our austamers to engage with their users at the right time. More over, being able to predict seword events chead, allows us to model intent, thereby explaining why a user will be performing a

Do you want to enrich your austome experience and deliver personalized and contest-owers engagement? Reach out to use.



VOLTIJDSE ARBEIDSOVEREENKOMST VOOR BEDIENDEN VOOR ONBEPAALDE TIJD

Anhah Ranjan Sta h

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Ashal Rejuision "

Pagina 213

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Artikel 8

Artikel 13

CEO

Opgemaakt in twee originelen te Antwerpen

op 23/03/2016

Gelezen en goedgekeurd (Gelezen en goedgekeurd)

De bediende (handtekening *)

Ashish Ranjan Jha

Pagina 313

Article 1

FULL-TIME EMPLOYMENT CONTRACT FOR UNDETERMINED TERM

BETWEEN:
Sentiance NV,
Hereinafter referred to as the "employer";
AND:
Ashish Jha:
Hereinafter referred to as the "employee";
THE FOLLOWING HAS BEEN AGREED UPON:

Page 113 Page 213



Sentiance NV Korte Lozanastraat 20-28 | 2018 Antwerp | Belgium www.sentiance.com | +32 3 359 95 96 | @sentiance

Article 9





Blog About

Text To Image Generation Using Generative Adversarial Networks

Generative Adversarial Networks (GANs) are a popular variant of the generative class of neural network models. The fundamental principle behind a GAN model is a discriminator and a generator model working against each other (roughly speaking) thereby achieving the ultimate goal of fine-tuning the generator to facilitate generating meaningful, non-random data.

READ MORE

Human Pose Estimation Using Deep Learning

This was my first ever deep learning project and so I am happy to share what I did there with some key insights. This is from 2014/15, when tensorflow didn't even exist. Theano did, though.

READ MORE

Deep learning for long-term predictions

Sentiance uses machine learning to extract intelligence from smartphone sensor data such as accelerometer, gyroscope and location. This intelligence comes in the forms of sensor based activity detection, map matching, driving behavior, venue mapping and more.

READ MORE

Using Neural Nets for Audio Events Detection

Audio events detection as the name suggests is the task of detecting 1 or more audio events in an audio clip of a certain duration. In this post, we limit our discussion to 1 audio event in an audio clip of a fixed duation of 4 seconds.

https://datashines.github.io

Eye Tracking Measures for Anthropomorphism in HumanRobot Interaction

Anthropomorphism is our tendency to attribute human like characteristics to non-humans animate or inanimate. In this study, I had the task of analysing anthropomorphism via eyegaze patterns as a human observed (i) human performing a task, vs, (ii) robot performing the same task.

READ MORE

Analysis and Subsequent Optimization of a Microcontroller Program

Having received the prestigious DAAD Scholarship, I got to do my Undergrad Summer Internship at OVGU, Magdeburg, Germany, on this interesting topic: Analysis and Subsequent Optimization of a Microcontroller Program for precise control of Pneumatic Valves used for Hot Wire Chemical Vapor Deposition I managed to modify an already existing program to increase the precision of the valves were actuated based on the microcontroller board multiplexed outputs.

READ MORE

Fundamentals of Finite Difference Methods

I had the opportunity to present on this topic at the 10th Indo German Winter Academy, 2011. Discrete mathematics has been one of my favorite areas of study in Mathematics. I was glad to be able to apply what I learned here later while studying Computer Graphics at EPFL.

READ MORE













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Your MBA Application Decision

Smartly Admissions <admissions@smart.ly> To: arj7192@gmail.com

Wed, Mar 13, 2019 at 10:35 AM





Hi Ashish.

Congratulations! On behalf of all of us at Smartly, I'm so pleased to notify you of your acceptance into the Smartly MBA - March 2019 class. We're delighted to have you join this outstanding group on a journey of learning and career advancement.

The week before classes begin you'll receive additional information from us to prepare you for the start of classes on Monday, March 25. If you have any questions before then, please let us know. Feel free to let your friends know the great news!

> I was accepted into Smartly's MBA program! # #Accepted #SmartlyMBA #DegreeBound: smart.ly







Congratulations again!

Sincerely, Matt Schenck VP of Smartly Admissions













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2019 - Finalists & Winners



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From one monolithic milestone to the next, civilizations may come and go. As we build *this* one—qualifying it through careful correction, ensuring progress, making mastery and advancement real—we awaken to our full potential.

We're it, the chance is ours—and for learners, leaders, and earnest students of the future—the future is bright.

Here's to those with their shoulders to the wheel.

(Finalists listed below - winners are marked with *)

FINALISTS & WINNERS BADGES AND PRESS RELEASE AVAILABLE HERE

NOTE: Beautiful TROPHIES are available for purchase for WINNERS as well as FINALISTS.

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NOTE:

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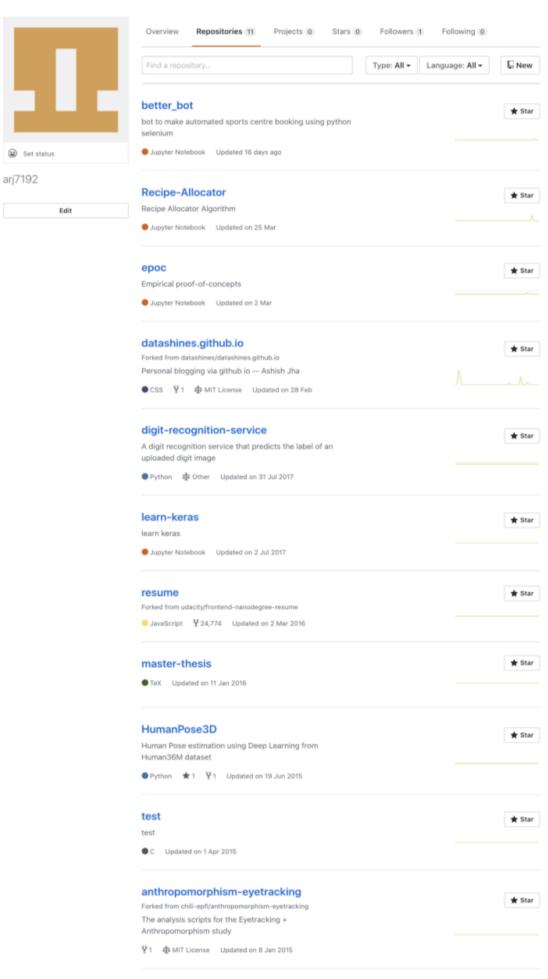
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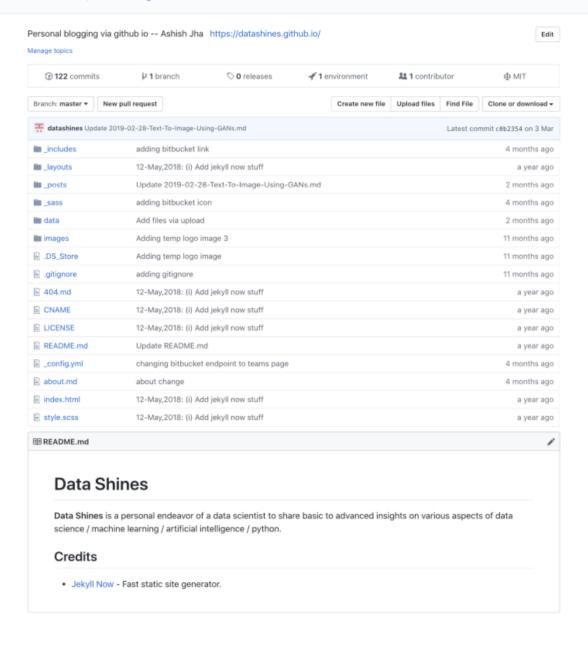
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| • | semantic_search_main semantic_search / datashines - 2018-12 | Webapp with semantic search on a document funtionality | | |
| 3 | flask hackDaemon2 - 2018-04-12 | | | |
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| (-) | api Untitled project / AARCTERN-ML - 2018 | Handling API calls. | | |
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