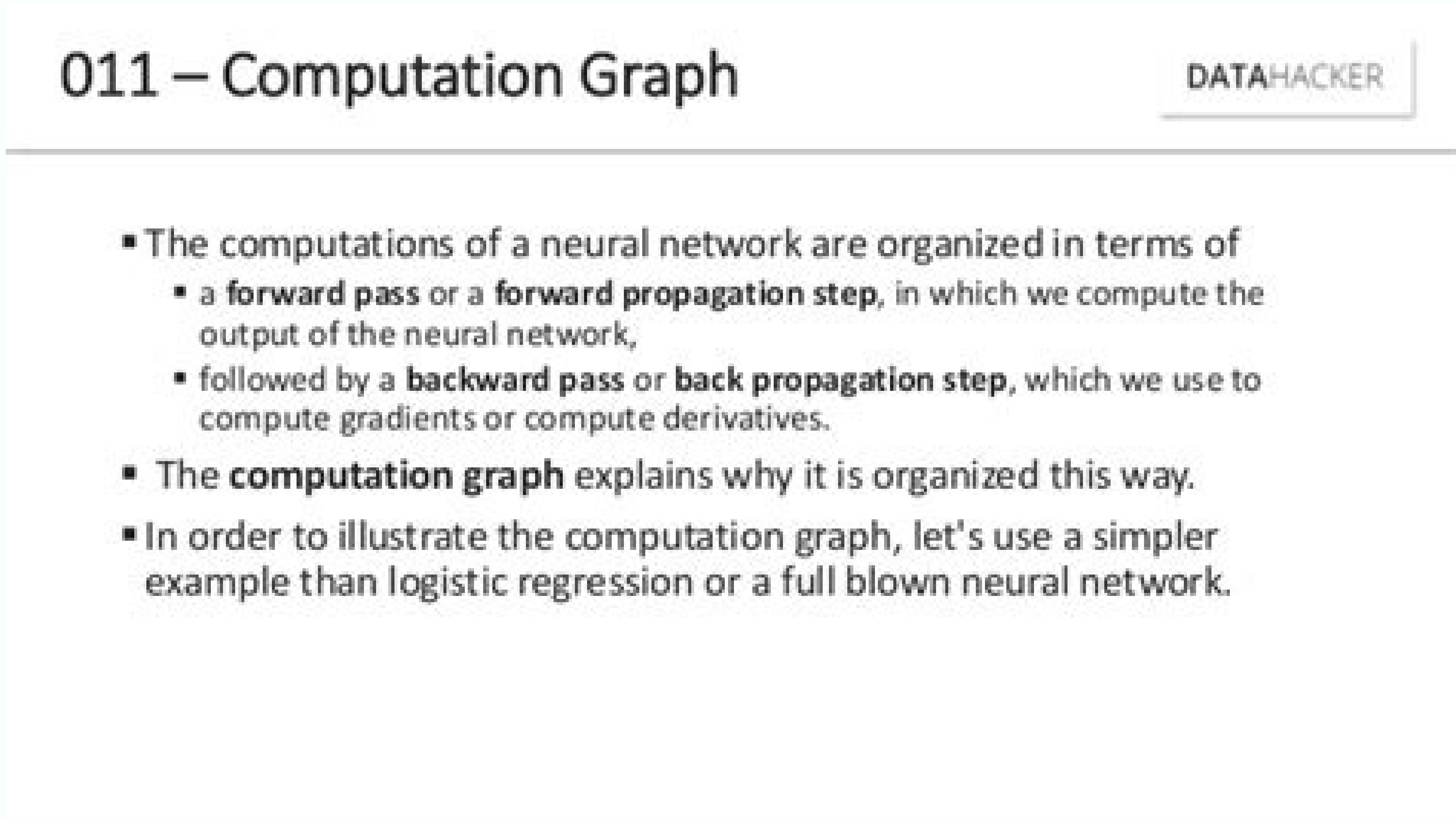
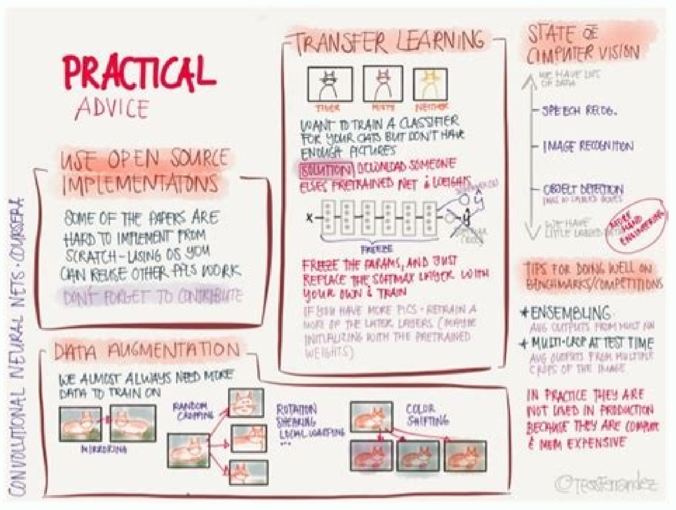
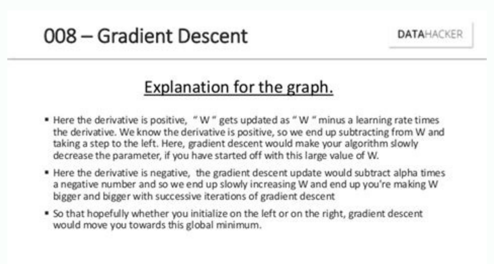
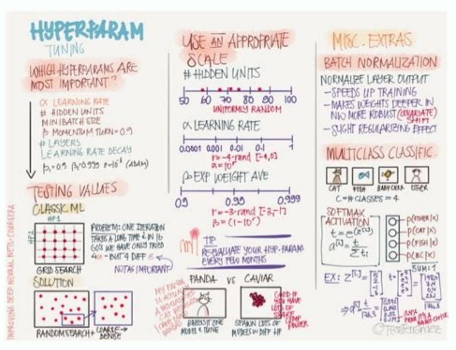
Andrew ng coursera deep learning notes pdf









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Learning program Description Learn a skill relevant to the work that you can use today in less than two hours through © is an interactive experience guided by an expert on the subject. Access everything you need in your browser and complete your project confidently, with step-by-step instructions. Take courses from the best instructors and universities in the world. The courses include lectures recorded with autonomic classifications and with peer reviews, lectures in vain and discussments in communities. When completing a course, you are qualified to receive a Shareable Electronic Course Certificate for a small fee. Sign up for a specialist to master a specific career skill. You will complete one sound © Series of rigorous courses, face practical projects and win a Certificate of Expertise to share with your professional network and potential employers. If you are going to learn on your own with the best companies and universities, apply your new skills in practical projects that show your experience to potential employers and gain career credentials to start your new career. With MasterTrack Certificates ®, Parts of the Mastermind programs have been divided into online hands, so that you can earn a high quality career accreditation issued by the university at an innovative price in a flexible and interactive format. Benefit from a profoundly involving learning experience with real-world projects and live and specialised tools. If you © accepted for the full master program, its MasterTrack course counts for its degree. Transform your curriculum with a diploma from a higher university for a revolutionary price. Our experience of modular degree learning gives you the ability to study on line at any time and earn credit © told how you complete your course assignments. You will receive the same credentials from the who attend class on campus. Courses cost much less than comparable on campus programs. Machine Learning Machinethe science of making computers act without being explicitly programmed. In the last decade, machine learning has given us self-driving cars, practical speech recognition, effective web searching, and a greatly enhanced understanding of the human genome. Machine learning isn't widespread today that you probably use it dozens of times a day without knowing it. Many researchers also believe that it is the best way to make progress MI at Human level. In this class, you will not learn about the most effective machine learning techniques, and I will gain practical by implementing them and making them work for you. More importantly, you will not only learn about the ³ foundations of learning, but you will also gain the necessary expertise to quickly and powerfully apply these techniques to new problems. Finally, you won't learn about some of the best innovation practices in the Valley of Success, since they refer to machine and AI learning.This course provides a broad introduction to machine learning, data analysis and µ recognition. ³ include: i) Supervised learning (algorithms stop ©tricos/no stop ©tricos, Supporting vector machines, nuclei, neural networks). (ii) Unsupervised learning (grouping, reducing dimensionality, systems of recommendation, in-depth learning). (iii) better automatic learning practices (µ/polarization theory; innovation in machine and AI learning). The course will also be based on numerous case studies and applications, so that you will also learn how to apply learning algorithms. construction of smart problems (perception, control), text understanding (web search, anti-spam), computer view, medical information, audio, database mining and other areas. source: [1]I recently enrolled for the deep learning specialization course offered by deplearning.ai, in And I watched almost all the video (at the rate of 1.75 reproduction with which I was quite comfortable) during the period of a free trial. Along the course, I annotated key points key points concepts explained by world-class instructor Andrew Ng. As I was also reading the very well-structured and clearly described assignments (in the form of Python notebooks), I tried to take note of the important concepts for which the assignment was designed. Now, as my first story on Medium, I'd like to share my notes, from which (Hopefully) other readers will benefit. As such, all figures and comments in this article are taken from the content of this course. To no surprise, the deep learning course taught by Andrew Ng and his team is an amazing course. In addition to learning and understanding neural networks and deep learning concepts, the course is coupled with deep programming assignments that allow course students to learn the fundamentals of neural networks and deep learning from scratch (e.g., forward and backward propagation, loss function, gradients, optimization, and many more). As you follow tasks one by one, you move to more sophisticated deep learning architectures (CNNs, RNNs) and end by the attention engine There are 25 programming assignments in total. I suppose you're already knowledgeable about machine learning, linear algebra, etc. The points and observations discussed here are those that I personally found important for someone willing to enter the field of neural networks and deep learning. I would also like to point out that I was experienced in neural networks and deep learning before taking this course. Okay, from now on, fewer words, more pictures: A picture is worth a thousand words. So let's get started. Course 1: Neural Networks and Deep LearningHere, the popular function of cross entropy loss is discussed as part of logistic regression, a binary classification algorithm. Specifically, note those green texts where the intuition behind the loss function is explained.source: [1]Explanation of the concept of gradient descent in a algorithm in neural networks. In particular, see how the weight update is done iteratively during gradient descent. Why do we need the gradients? Move to ³.Source: [1] The clearest explanation I see about the intuition of derivatives that play an important role in optimizing neural networks. Approximately speaking, the derivative is the inclination of the fun: Therefore, the factor F (a) will change when an© is slightly changed.Source: [1] The popular µ of active are portrayed. Note that Ã¢ â¬ "sigmoid Ã¢ â¬ Ã¢ â ¬" pushes the input to the range [0, 1], and Ã¢ â1 A problem with these two types of active µ: when the transformed values are at the extremes, the derivatives are quite small, giving the problem of vanishing gradients. Reluµfamiliar assets are most often used that do not suffer from this problem.Source: [1] here, It has been explained why we need to µ active fun in neural networks, this is, to introduce non-linearity. It is explained that without using an active function, the network effectively learns a linear model.Source: [1] It has been shown that the simple log return is a surface network (vs. deep) spp. You will also be ©m There are three types of layers in neural networks, that is, input layer, hidden layer and layer of solution. A deep network is actually a network with many hidden layers.source: [1] The network pairs are "weight and prejudices" for different ³ that must be learned. On the other hand, the hyper-parameters are those that affect the learning procedure, the most important thing is the learning rate (remember the role of the learning rate in the descent of the gradient) .Source: [1] The neural network training procedure takes the following steps iteratively: µ Making a forward pass and producing predictionsCompare predictions µ the values of the truth of the soil using the loss fun producing the errorerror is propagated from behind across the network, compensating for theto adjust the parameters (the gradient of each layer is based on the gradients of the previous layer) Course 2: Improve Deep Neutral Networks: Hyperparameter tuning, Regularization and OptimizationRegularization is a technique to avoid overadjustment, a scenario where the learned model has a good performance in the training data, but a poor performance in the unseen data (tests) (i.e. the model suffers from low polarization, high variation). L2 regulation is a technique that is based on the assumption that a model with small weights is simpler than a model with larger weights. Here is the intuition behind the l2-regularization that encourages weights with small values (near to zero). The term regularization is that purple text added to the cost function (lost). Source: [1]Dropout is another very popular regularization technique. In this type of regularization, nodes (neuronics) do not participate in the training with some probability. The intuition behind the withdrawal is that the network cannot rely on any feature (no) so it needs to spread the weights. Notes: The abandoned neurons do not contribute to the training both in the propagation to the front and back. We should use the "only" abandonment during training. Source: [1]To avoid over-equipment, getting more training data can help, but it is expensive. One thing we can try is to increase the training data in hands, using data-increasing methods. For example, in the case of images, one can apply mirroring, random cutting, color change, rotation, etc. Source: [1] Early-stopping is another technique to avoid overfitting, that is, we stop model training since validation error begins to diverge from training error. source: [1]The standardization of characteristics is a common stage of pre-processing before feeding the data on neural networks. We normalize the characteristics so that each feature is transformed into a zero average, andof the standard deviation of the unit. The main hopeful by rafters of standardization is that she can lead to more fastested formation. See why this is the case, if, [1]One of the problems we can encounter in the form of deep networks is that the derivatives (slopes) can become extremely small or large, which are known as escape gradient and explosion problems (respectively). A careful ³ of weights can help to get rid of these problems.source: [1]A few other points to take into account about the ³:Initializes different µ give different results.weights must be randomly initialized to break the symmetry in the network. For example, if all weights are initialized with zeros, then the network cannot learn since all hidden units are doing the same thing, so it cannot break symmetry. A whole called "Initialization" (named for the first author of He et al., 2015) works well for networks with active µes ReLU.source: [1]In order to deal with the explosion of gradients, an option will not use the clipping of gradients, that is, clipping the gradients to be within a pre-specified range.source: [1]Gradient checking There is a technical problem that can help to verify that the backpropagation is working properly. To do this, we first do the following:source: [1]We then perform the gradient check as follows:source: [1]By fine-tuning the hyperpandometers of the network (e.g. learning rate, number of layers, number of units per layer, etc.), it is recommended to use ³ search instead of grid search, as you can search for the set of meters you may not be able to explore during grid search.source: [1]Standardizing all the features before feeding the network can help speed up learning. So, with this in mind, we will like to do the same thing for values in hidden units. This process is called Batch Normalization.source: [1]Softmax layer Normally the last layer in the networks for classification As in the case of log returns (for binMania) It produces a probability distribution (so the values add to 1) that tell us how likely the input example belongs to each class. Source: [1] course 3: structuring machine learning projects jumped into this course as it was mainly about how to Build successful machine learning projects. Course 4: Convolutive neural networks that are about deep learning about images, using classical neural networks (MLPS) are prohibitive, i.e. we end up with a very large number of parameters to train. Source: [1] Thus, convolutive neural networks (CNNs) come to rescue. The convolution operation is one of the main building blocks of the CNNS. Below is an example of a 3*3 filter (A.K.A., kernel) that moves over the image to extract resources, called resource-convolved. The application of a size filter (f*f) in a size image (n*n) would leave us with size convenipt characteristics (N-F + 1) * (N-F + 1) .Source: [1] different Filters can learn different features. For example, the following demonstrates how the filter can be used to detect vertical edges in the image. However, note that these filters are usually learned during training, so that they are not chosen by hand. [1] Using filters: Every time we involve, the resources involved shrinked. Pixels in corners (sides) are much less used At the exit, playing so much information. To address these issues, the filling is used, i.e. the edge of the image is padded with zeros. Applying a size filter (f*f) in a size image (n*n) with the p fill would leave us with sizesource convenipt features: [1] during the convolution operation, the Stride is the value you move the window every time you move the window slide. Here is an example in which a size input (7*7) is convoluted with a filter (3*3) with the Stride = 2, whichin a size out (3*3). In general, for a size image (n*n), size filter (f*f), p fill and step S, the convoluted features are of Sizefloor ((N + 2P-F) / S + 1) * floor ((n + 2p-f) / s + 1) Source: [1] illustration of over volumes using multiple filters:source: [1]CNNs use pooling to reduce the size of the characteristics in question, and also create more robust characteristics. At most pooling, the maximum value of the filter is extracted. Another alternative is to apply average pooling.source: [1]The size of the f filter, the stride s, and the type of pooling operation serve as the hyper-parameters of the pooling layer. Grouping layers have no parameters to learn, but still participate in backpropagation to calculate layer gradients before.source: [1]Here's what happens in a convolutional neural network layer:Apply filters on the inputApply relu activationDelete the activation source: [1]In general, there are three types of layers in convolutional networks: Convolution (CONV)Pooling (POOL)Fully connected (FC)Here is an example of deep CNN. Note that as we deepen in the network, the size of the characteristics decreases (those with green border), while the number of channels increases (those with purple border).source: [1]An example of CNN inspired by LeNet-5 (created by Yann LeCun). The network input is handwritten digits with three channels, namely RGB. Note how different layers are stacked together.source: [1]Here is the number of parameters within each layer of an example CNN:source: [1]As mentioned earlier, using convolutions instead of classical neural networks (MLPs), we greatly reduce the number of parameters to train the network. In addition, the convolutions bring us the following benefits:source: [1]It is useful to look at some CNN case studies to get an idea of how we can build our own CNN.source:[1]source: [1]Due to escape\/explosion gradients, very deep neural networks are difficult to train. Residual Networks (ResNets) allow you to build and train very deep neural networks, passing the activation to the following layers, that is, using the residual block. can see how the activation follows the way to the shortcutan ¢ instead of ous roP .odassap od seµÃ§Ãamrofni sa m©Ãtnam e lauta opmet ed apate an seµÃ§Ãamrofni sa eceuqse ,0 a omix³Ãrp ¡Ãtse odnauQ .1 uo 0 a somix³Ãrp serolav avel ,sosac sod airoiam aN .odassap on uo)air³Ãmem ed alul©Ãc(lauta alul©Ãc an saditnam res meved seµÃ§Ãamrofni sa es ediced euq o£Ã§Ãazilauta ed atrop a ©Ã sURG sad evahc etnenopmoc O .ratagser arap mªÃv)sURG(seµÃtroP moc setnerroceR sedadinU ,ozarp ognol ed saicnªÃdneped ed amelborp o revloser araP .sÃ Ã´o£Ãsiverp ad opmet ed ossap od otrep ¡Ãtse euq o£Ã§Ãamrofni ,©Ã otsi ,lacol o£Ã§Ãamrofni an esab moc atsiverp res edop y adÃas adac odnauq rohlem manoicnuf selE)setna salul©Ãc satium me o£Ã§Ãamrofni ad edneped t opmet ed ossap on o£Ãsiverp a ,©Ã otsi(t opmet ed ossap on o£Ãsiverp rezaf arap ozarp ognol ed saicnªÃdneped ¡Ãh odnauq ,ralucitrap mE .aguf ed setneidarg ed samelborp martnocne ,sovitacilpa snugla arap ohnepmesed mob mu mahnet arobmE:sNNR erbos satoN]1[:etnof:NNR ed sopit setnerefid metsixE]1[:megiro:artuo a s³Ãpa amu salul©Ãc sasse mahlipme sNNR sA]1[:etnof.NNR alul©Ãc amu ed ortned odnecetnoca ¡Ãtse euq o rev Ã Ã .t lauta opmet ed apate an y o£Ãsiverp a e)otluco odatse(a o£Ã§Ãavita a o£Ãs sadÃas sA .odassap od seµÃ§Ãamrofni sa odnetnoc)otluco odatse ,ajes uo(1-t roiretna opmet ed apate ad a o£Ã§ÃavitAt opmet ed apate an x lauta adartnE:alul©Ãc adac ed sadartne sA .etnemaditeper)sedadinu(NNR salul©Ãc masu setnerrocer siaruen sedeR]1[:etnof.artuo arap alul©Ãc amu ed seµÃ§Ãamrofni sa odnassap :aicnªÃuqes ed sodad ed seµÃ§Ãisop setnerefid me sodidnerpa sosrucer mahlitrapmoc seder sasse ,)sPLM(saciss¡Ãlc siaruen seder sad oir¡Ãrtnoc oA .)sNNR(setnerroceR siarueN sedeR ,.e.i ,aicnªÃuqes ed sodad arap sadauqeda o£Ãs euq siaruen seder ed etnairav etnatropmi artuo erbos somalaf ,iuqAaicnªÃuqes ed soledoM :5 osruC]1[:etnof.sadamac siam odnanoicida ,eder ad edadidnuforp a somatnemua euq adidem Â odnizuder aunitnoc otnemaniert ed orre o euq odartsom Ã .steNseR sadamahc sadnuforp otium seder aurtsnoc ªÃcov euq etimrep siaudiser socolb sessed sotium rahlipmE]1[ )MTSL( )MTSL(ozarp ognol ed air³Ãmem ed sedeR]1[:etnof.oir¡Ãrtnoc o zaf ,1 ed otrep ¡Ãtse odnauq ,odal the generalized version of the GRUs, and even more powerful to maintain long - term dependencies. The following doesn't show you any more intuitive than I've ever seen, where you've shown what's going on in the heart of an LSTM.source cell: [1]In words:The hidden state of the previous time step (a) and the input of the current time step (x) are concatenated and multiplied by the Wf weights of the forgettable port, followed by the application of the fun to the sigmoidÃ¢ to have values in [0, 1] such as the sa (Gamma_f) of the forgettable port.Multiply (Gamma_f) element-wise with the state of the previous cÃ ©lula (c)© how to apply a Message about the state of the previous Chapter. If a unit in (Gamma_f) is ³ 0, then the respective unit in (c) will be forgotten. On the other hand, when a unit in (Gamma_f) is ³ 1, it is probable that the information in the corresponding unit in (c) is kept in the next step³value of the candidate (c_tilde), containing values in the range [-1, 1], it is not in the current step of time that can be kept in the current state of the squid (c). The decision is made by the update port (Gamma_i). The update port (Gamma_i), containing values in [0, 1], Is multiplied by element-wise with the value of the candidate (c_tilde). again how to apply a mask over the candidate's value (c_tilde) to decide what to include or exclude from the state of the squid (c). When a unit in (Gamma_i) is ³ 0, this implies that the corresponding unit in (c_tilde) will not be passed to the state of the squid (c). On the other hand, if a unit in (Gamma_i) is ³ 1, this leads to including the corresponding unit in (c_tilde) in the state of the cÃ ©lula (c). The state of the cÃ ©lula (c) Ã© the Ã³riaÃ¢ of the cÃ ©lula that can be used in subsequent time steps. The port of sa (Gamma_o), containing values between 0 and 1, predicts the current time step. 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