A MODEL OF SEMANTIC COMPLETION
IN GENERATIVE EPISODIC MEMORY

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ABSTRACT

Many different studies have suggested that episodic memory is a generative process, but most computational models adopt a storage view. In this work, we propose a computational model for generative episodic memory. It is based on the central hypothesis that the hippocampus stores and retrieves selected aspects of an episode as a memory trace, which is necessarily incomplete. At recall, the neocortex reasonably fills in the missing information based on general semantic information in a process we call semantic completion.

As episodes we use images of digits (MNIST) augmented by different backgrounds representing context. Our model is based on a VQ-VAE which generates a compressed latent representation in form of an index matrix, which still has some spatial resolution. We assume that attention selects some part of the index matrix while others are discarded, this then represents the gist of the episode and is stored as a memory trace. At recall the missing parts are filled in by a PixelCNN, modeling semantic completion, and the completed index matrix is then decoded into a full image by the VQ-VAE.

The model is able to complete missing parts of a memory trace in a semantically plausible way up to the point where it can generate plausible images from scratch. Due to the combinatorics in the index matrix, the model generalizes well to images not trained on. Compression as well as semantic completion contribute to a strong reduction in memory requirements and robustness to noise. Finally we also model an episodic memory experiment and can reproduce that semantically congruent contexts are always recalled better than incongruent ones, high attention levels improve memory accuracy in both cases, and contexts that are not remembered correctly are more often remembered semantically congruently than completely wrong.

Keywords
Generative episodic memory · Semantic completion · Computational memory model · Scenario construction ·

Introduction

Episodic memory is hippocampus dependent and enables us to remember personally experienced events [1], semantic information on the other hand is represented in higher cortical areas and captures general facts and regularities of the world around us [2]. Early concepts of episodic memory were based on the storage model, according to which the content of the memory more or less faithfully reflects the content of the experience [3]. This view is oversimplified since it reduces episodic recall to a mere readout process of stored complete information. However, overwhelming empirical evidence suggests that the recalled memories can be influenced both by past and future information as well as the context of encoding and recalling. Pioneering studies have suggested that semantic interpretations, rather than sensory inputs, are stored in memory [4, 5] and that memories are reconstructed during recall [4]. In word list studies using the Deese–Roediger–McDermott (DRM) paradigm [6, 7] participants “remember” semantically related words that were not on the study list when asked to retrieve the words studied earlier. There is also evidence that semantic and episodic memories interact and complement each other during retrieval [8]. For instance, Devitt et al. [9] have found in a meta-analysis of eight studies based on autobiographical interviews that when subjects report an episode, their usage of “internal” (episodic) details and “external” (semantic) details are negatively correlated. The subjects use semantic
information to compensate for insufficient episodic detail in their memory. Other examples are experiments by Barlett [4], where subjects of non-matching cultural background recalled folk tales. The recalled stories were distorted to match the subjects’ cultural background (semantic information). Finally, there are also paradigmatic examples of memory adjustment due to social context [10, 11], self-model [12], stress [13], and many other factors [14, 15].

Few contemporary researchers would oppose the idea that episodic memory is – at least to a certain degree – generative in nature [8]. Nonetheless, most of the existing computational models (including some of our own [16, 17, 18]) adopt the storage view, where memories are preserved and later retrieved faithfully [19, 20, 21]. Such models are usually tested with either random patterns or abstract spatial representations [19, 20, 21, 17, 18] but not with realistic sensory input. With such artificial input patterns, it is rather suggestive to think in terms of mere storage (VAE) as a model for memory [25]. A VAE is an autoencoder architecture that maps input images to a plain Gaussian (ii) to discard some of the input patterns during storage to model the inevitable loss of information in the brain due to the attentional bottleneck, and (iii) to include a generative element in the model that is able to reasonably fill in the missing information. Discarding some of the input patterns can be done in at least two ways, by lossy compression and by selection (either before or after compression). The former refers to a process like mp3 encoding, a compression that tries to discard only the information that is irrelevant or recoverable from what is being stored. The latter refers to a process where some part is selected for storage and another one is discarded altogether, e.g. from a picture of a water mill at a creek the mill could be attended to and stored while the creek could be ignored. When recalling the mill, our semantic system probably complements it by a creek, but the creek might look very different from the original one, and we are probably not even aware of this, a process we refer to as scenario construction [22]. When recalling the mp3 encoded song, on the other hand, there might be some noise due to the strong compression, but all in all the song is faithfully reconstructed. We refer to the representation reduced by compression and selection as the gist that is stored in a memory trace and from which the original episode can be reconstructed, either quite faithfully if only compression is involved or at least plausibly if also selection is involved.

In order to model the generative process of episodic memory recall we believe it is important (i) to use (real-world) input patterns as stimuli with enough structure that can be exploited by a semantic system for a generative process, (ii) to discard some of the input patterns during storage to model the inevitable loss of information in the brain due to the attentional bottleneck, and (iii) to include a generative element in the model that is able to reasonably fill in the missing information. Discarding some of the input patterns can be done in at least two ways, by lossy compression and by selection (either before or after compression). The former refers to a process like mp3 encoding, a compression that tries to discard only the information that is irrelevant or recoverable from what is being stored. The latter refers to a process where some part is selected for storage and another one is discarded altogether, e.g. from a picture of a water mill at a creek the mill could be attended to and stored while the creek could be ignored. When recalling the mill, our semantic system probably complements it by a creek, but the creek might look very different from the original one, and we are probably not even aware of this, a process we refer to as scenario construction [22]. When recalling the mp3 encoded song, on the other hand, there might be some noise due to the strong compression, but all in all the song is faithfully reconstructed. We refer to the representation reduced by compression and selection as the gist that is stored in a memory trace and from which the original episode can be reconstructed, either quite faithfully if only compression is involved or at least plausibly if also selection is involved.

Following the lossy compression approach from a perspective of rate-distortion theory (RDT) and efficient coding, Bates and Jacobs [23] as well as Nagy et al. [24] have modeled perception and episodic memory as a generative process. Bates and Jacobs have argued that a capacity-limited perceptual system like the brain should use prior knowledge and take into account task dependencies to compress the input into an optimal representation. Nagy et al. have demonstrated that systematic distortions in memory are similar to the distortions that are characteristic of a capacity limited generative model adapted to an environment for compression. They use a Variational AutoEncoder (VAE) as a model for memory [25]. A VAE is an autoencoder architecture that maps input images to a plain Gaussian model distribution and back again to images. Episodic memory can then be modeled by storing the location in the Gaussian as a memory trace, which is a low-dimensional feature vector. From such a memory trace the full image can be reconstructed. The lossy compression from input to Gaussian is so extreme in this case that memory recall is largely generative. It is even possible to generate new images without any input or memory trace by sampling from the Gaussian and then decoding this vector. Any such image looks similar to the images seen during training, in fact the system can only represent such seen images or interpolations thereof. These models are already generative but with a focus on optimal compression while our focus is semantic completion.

The model we propose here is built on a Vector-Quantized Variational AutoEncoder (VQ-VAE) [26], which, despite the similarity of the names, works quite differently from a VAE. It transforms input images into an array of low-dimensional feature vectors (rather than just one) and thereby maintains some spatial resolution. This has two great advantages: (i) We cannot only model compression but also spatial selection by attention. We do that by discarding some fraction of the feature vectors in the array and keeping the rest. (ii) The model can also store and recall input patterns that are quite different from those seen during training because the known feature vectors can be combined in many different new spatial constellations. For instance, a VQ-VAE trained on digits 0 to 4 can also represent digits 5 to 9, a VAE cannot do that. We see another advantage of the VQ-VAE for our purposes in that the feature vectors are quantized, which is in analogy to semantic categorization in the brain.

However, the VQ-VAE is not generative. Thus, we add a Pixel Convolutional Neural Network (PixelCNN), which is able to fill in missing feature vectors in the array of vectors, up to the point that it creates entirely new arrays from scratch. Conceptually this model is able to fill in a creek to complement the mill, but we use much simpler stimuli (namely handwritten digits from the MNIST database) for our simulations for computational efficiency.

The VAE, the VQ-VAE, and the PixelCNN in the models above are trained on large sets of images and thereby capture the statistical regularities in them, which we consider to be semantic information. The VAE and VQ-VAE
capture the semantic information needed to do and undo the compression; the PixelCNN captures the semantic
information required to fill in neglected parts. The term semantic might seem overly ambitious here, but we believe that
the semantic information these generative models capture shares essential characteristics with what we would normally
refer to as semantic, namely general regularities of the world that hold beyond and are represented independently of
particular episodes. Furthermore, in the VQ-VAE the semantic information is quantized, i.e., discrete in nature, which
resembles categorization.

One might think that a storage memory would be advantageous over a generative one because of its faithfulness.
However, scenario construction during recall is essential to the etiological function of episodic memory, because it
provides far more flexibility to deal with missing data and to adjust to variable demands and constraints than a faithful
reproduction of past experiences could. Moreover, the already acquired semantic knowledge can help to improve the
storage efficiency of the memory. Put simply, generativity is a useful feature in episodic memory, not an aberration[27].

**Computational model of generative episodic memory**

Based on a biologically-motivated conceptual framework and using methods from machine learning, we have
developed a computational model that allows us to investigate semantic completion in a generative episodic memory on
real world images on a fairly abstract level but still in analogy to concrete brain structures, so that predictions on a
behavioral level but also about neural processes are possible.

**Conceptual framework**

We hypothesize that generative episodic memory works as follows:

1. Sensory input patterns that make up the episode are perceived by a hierarchically organized network and
   transformed into a hierarchical perceptual-semantic representation in cortical areas, such as the visual system.
2. Some elements of this representation are selected for storage in episodic memory. We call this the episodic
gist.
3. The episodic gist is stored in hippocampal memory as pointers to the corresponding perceptual-semantic
elements in cortical areas. We call this the memory trace.
4. Triggered by some external or internal cue, or even spontaneously, the memory trace can be reactivated.
5. The pointers in the memory trace reactivate corresponding perceptual-semantic elements in cortical areas.
6. Semantic information in the cortical areas complement the reactivated elements by means of a recurrent
dynamics to construct a plausible full representation from the incomplete gist stored in the memory trace.

Several of these steps and concepts deserve closer consideration.

- We speak of a perceptual-semantic representation, because (i) we consider the transformation from the raw
  input to a high-level semantic representation a gradual process, as is well known for deep neural networks, and
  (ii) we believe that we can actually remember also quite low level aspects of an episode, such as the exact
  color and shape of an object. So, we believe that there is no clear cut distinction between perceptual and
  semantic representations.
- The concept of gist is well known [28, 29, 5]. The episodic gist [16] contains essentials about the episode that
  are selected dynamically depending on attention and the context [30]. They may be detailed in some cases and
general and vague in others.
- Episodic memory traces are pointers to perceptual-semantic elements of the sensory input rather than the
  representations of the input itself [31].
- Semantic information is usually extracted from multiple experiences, is mostly categorical, and refers to the
  prototypical properties of objects or people and their relationships [3, 32]. Evidence from patients with
  semantic dementia suggests that semantic information is vital for episodic memory recall [33].
- Because of its generativ nature, we call the retrieval process scenario construction.

Our computational model does not yet capture all aspects of this conceptual framework, but we believe it is a good first
step in the right direction.
Network architecture

Our computational model consists of two networks known from the field of machine learning, a Vector-Quantized Variational AutoEncoder (VQ-VAE) [26] and a Pixel Convolutional Neural Network (PixelCNN) [34], see Figure 1.

![Network architecture diagram](image)

**Fig 1. Network architecture.** The encoder, which consists of several convolutional layers, compresses the input image into an array $z_e$ of $w \times h \times d$-dimensional feature vectors. Each feature vector is then assigned to the closest codebook vector $e_l$ to create the index matrix $z_x$ containing the indices $l$ and an array $z_q$ of $w \times h$ corresponding $d$-dimensional codebook vectors $e_l$. The decoder then reconstructs the original input based on the quantized array $z_q$. Attention is modeled by discarding consecutive entries in the lower part of the index matrix. The missing part can be filled in by the PixelCNN in a recurrent process that performs semantic completion. The completed index matrix is then passed to the decoder for reconstruction.

A VQ-VAE consists of an encoder, a decoder, and a latent representation between these two. To quantize the latent representation there is also a set of codebook vectors, which are optimized by vector quantization but otherwise fixed. The VQ-VAE processes an input image in the following steps, cf. Figure 2:

1. The VQ-VAE first compresses the image of size $28 \times 28$ (or $32 \times 32$ for images with context) with a convolutional neural network (the encoder) down to an array of $w \times h \times d$-dimensional feature vectors ($w = h = 7$ for the original images and $w = h = 8$ for images with context, $d$ is set to 64). The positions within the array correspond to a grid of subsampled locations in the image. Thus, this array still has a coarse spatial resolution, and the feature vectors are a description of the image around these locations.

2. This array is then converted to an array of $w \times h$ indices (called index matrix for short), each index indicating the $d$-dimensional codebook vector most similar to the feature vector at that position. This can be viewed as a quantization step that makes the representation more categorical, i.e. more semantic. Up to this point the network has compressed the image into a more abstract and semantic representation.

3. In order to recover an image back from this highly compressed latent representation, the array of indices is converted to an array of the corresponding codebook vectors, which should be similar to the array of feature vectors of Step 1.

4. The array of codebook vectors is then decompressed by a deconvolution neural network (the decoder mirroring the encoder) to produce an image of original size.

A VQ-VAE alone can convert an image into a more abstract and semantic representation and back again, but it is not generative in the sense that it could produce new reasonable images from scratch or complement incomplete images.
This is fine as long as the full index matrix is available. However, we also want to model attentional selection, so that only part of the index matrix can be recalled from memory. In such cases we need a generative component that is able to fill in the missing indices. For that we use a PixelCNN.

A PixelCNN is a probabilistic autoregressive generative model that is able to continue sequences of numbers. It can fill in missing pixel RGB-values in an image in a fixed sequence, for instance row-wise from top left to bottom right. If the first lines of an image are given, the PixelCNN can continue the sequence of pixel RGB-values and fill in the rest of the image reasonably well. Since the PixelCNN is designed to continue sequences and not to fill in missing pixels, it can only work in the one order it has been trained for, here from top left to bottom right. It cannot take advantage of known pixel values in the bottom right corner for other pixels in the image. Completing an image with a PixelCNN is a very time consuming process. We apply the PixelCNN not to the image but to the latent index matrix, which is much faster, to train the network and to apply the trained network. Since a PixelCNN only works in one particular order, we can model attentional selection only in a primitive form by keeping the upper rows and neglecting the lower rows of the index matrix. The level of attention determines how many rows to keep.

The VQ-VAE as well as the PixelCNN are both trained on a large set of training images. First the VQ-VAE is trained to reconstruct the input images as well as possible, despite the strong compression in the latent representation. The weights of the encoder and decoder are optimized as well as the codebook vectors. Once the VQ-VAE is trained, the PixelCNN can be trained on the index matrices generated by the trained VQ-VAE from the training image. See the Methods section for further details on the VQ-VAE and the PixelCNN.

Our model is designed to reflect our hypothesis on generative episodic memory. That is, the stored gist has far less information content than the input images; nonetheless, the input can be reconstructed from it. The model captures complex statistics from the input and also reflects the constructive nature of episodic memory that has been observed in many studies. When the attention is low (only a small part of the index matrix is stored), the recalled memories are not necessarily faithful. Still, they are valid and likely reconstructions of the original data. The model is also capable of dreaming, i.e., generating unseen but valid episodes.
Analogy to the brain

Even though VQ-VAE and PixelCNN originate from the field of machine learning, we believe they capture essential aspects of neural processing in the brain, and they are an appropriate level of description for our purposes here.

The encoder network of the VQ-VAE corresponds to the feedforward processing in the visual system, which results in abstract object representations in the inferior temporal (IT) cortex. Many studies have discussed a correspondence between the hierarchy of the human visual areas and layers of CNNs [35, 36, 37]. The decoder has a structure symmetrical to the encoder and is similar to the feedback connections from higher levels of the visual system to lower ones. It has been shown that during retrieval, a cortical representation of the memory is formed in the lower levels of the visual pathway through the feedback connections [38, 39]. Some studies have actually used an autoencoder structure to model the feedback connections in the visual pathway [40]. In our model, the decoder generates a cortical representation of the memory in its layers down to image level, which we take as a readout of the cortical representation of the memory during retrieval. A body of research also indicates that there is semantic learning at the level of the visual system, reflected in our model by the whole VQ-VAE network[41].

The PixelCNN learns statistical relationships between the elements of the latent representation of the VQ-VAE by repeated exposure, i.e. it learns semantic information from episodes akin to how it is hypothesized also for the brain [42]. It is then able to fill in missing elements in the semantic representation of an image. We hypothesize that this is akin to a recurrent dynamics in the higher cortical areas that can fill in missing information in a semantically consistent and expected way [43, 44].

We do not model storage in and retrieval from the hippocampus explicitly, we simply store and recall a perfect copy of the selected parts of the index matrix, which represents the episodic gist. Storing just the indices of the codebook vectors, and not the vectors themselves, is consistent with the indexing theory of hippocampal memory[45], although we would argue that our indices are also represented in the cortex, so that semantic completion can take place there.

Results

Our model is able to process real-world images and we believe that sufficiently rich statistical structure in the input patterns is essential for a meaningful simulation of episodic memory. However, large images require large data sets and are computationally expensive to process. As a compromise we use the well known MNIST data set of hand written digits [46], which is real-world, has a clear structure of ten digit classes 0 to 9, and is of moderate size, so that simulations can be conducted efficiently. The images show white digits on black background with gray values normalized between 0 and 1 and $28 \times 28$ pixels. First we illustrate the behavior of the system and then model a concrete memory task and compare it with experimental results [47].

Scenario construction by semantic completion

At the core of our model is the concept of an episodic gist, which is incomplete but can be complemented by semantic information to reconstruct a full scenario from a partial memory trace. What is being stored in the memory trace, i.e. what makes up the episodic gist, is largely determined by attention. In our model, attentional control is somewhat constrained and only determines how many consecutive indices of codebook vectors are stored row-wise starting in the upper left corner. For low attention only the upper two out of eight rows might be stored; for high attention the upper six rows might be stored. The remaining part, if needed, has to be constructed based on semantic information. It is important to note that attentional selection does not apply to the images but to the latent representation in form of the index matrix.

To illustrate the effect of semantic completion we have compared recalled images from memory traces at several different attention levels, see Figure 3. The first line is the reconstruction without semantic completion and the next lines are three different reconstructions with semantic completion. At high attention, the reconstruction is faithful; at low attention, the reconstruction is not necessarily faithful but it is plausible given the attended parts.

Improved memory efficiency by semantic completion

As mentioned earlier, the memory efficiency in our model is due to two factors: (i) the compression by the encoder network of the VQ-VAE and (ii) the semantic completion by the PixelCNN. The former reduces the storage requirement in our model already by a factor of 30 with little loss of image information, cf.[48]. Here we want to address the latter factor. To do so, we have to measure recall performance. Even though the mean squared distance between original image and recalled image is an obvious and frequently used measure, it is not very useful as a measure of perceptual similarity[49]. We have therefore trained a classification network (see the Methods section) to recognize
Fig 3. Semantic completion. Incomplete latent representations in the form of the index matrix are completed by the PixelCNN through a process we call semantic completion. The index matrix is already 30 times smaller than the image and only part of that representation is selected by attention. The attention level is defined as the percentage of the index matrix that is stored in the memory trace. The partial patterns in the first row visualize the episodic memory traces. The next three rows visualize three instances of the semantic completion based on the incomplete memory traces.

Fig 4. Semantic memory helps to increase the classification accuracy and capacity efficiency. Left: A classifier trained on MNIST is used to evaluate the classification accuracy on recalled patterns of different attention levels. The stronger the PixelCNN with its semantic information the better the accuracy for any given attention level. Right: For any expected classification accuracy the stronger PixelCNN requires less attention.

the ten digits and evaluate the quality of recall by the classification accuracy, i.e. the percentage of correctly recognized recalled patterns.

Figure 4 shows how semantic completion can improve memory efficiency. We have run simulations with semantic completion by a fully trained PixelCNN, by a partially trained PixelCNN, and without semantic completion at all, which we refer to as strong, weak, and none (semantic completion), respectively. The strong network was trained for 40 epochs and had a loss of 0.65 (categorical cross entropy), the weak network was trained for 3 epochs and had a loss of 0.75, and for the none case the not attended parts were just filled black. The left panel shows the improvement of the classification accuracy by semantic completion for fixed attention levels; the right panel shows the saving in attention level by semantic completion for fixed classification accuracy levels. We see that semantic completion can significantly contribute to recall quality (left panel) or capacity (right panel) although the memory saving is not nearly as large as for the compression by the encoder, maybe a factor of two.

Semantic learning at the level of the VQ-VAE

Semantic learning within the VQ-VAE has two aspects: the semantic learning within the neural representations of the encoder and decoder used for efficient compression and the categorization of the feature vectors by vector quantization.

Figure 5 shows how the semantic learning contributes to robustness to noise. Classification performance is compromised by pixel noise. The compression-decompression performed by just the autoencoder part of the VQ-VAE,
i.e. without the quantization, already reduces noise and improves performance; quantization improves performance even further.

The noise reducing effect of autoencoders is well known[50]. The quantization process in addition drags the internal representations towards what is know, what it has seen before, and this helps it in becoming more robust to noise, because noise moves the latent representation away from the normal distribution, while quantization drags it back, imposing a denoising effect.

![Fig 5. Effect of autoencoding and quantization on noise reduction and classification performance.](image)

Test images with different noise levels (left column) are processed by a VQ-VAE without (middle column) and with (right column) vector quantization. An MNIST classifier is then used to determine the classification accuracy of the reconstructed images. The right panel shows the classification accuracy for the three settings against input noise ratio. The VQ-VAE network achieves highest classification accuracy for its reconstructed noisy inputs.

The latent representation in a VQ-VAE still has some spatial resolution and can take advantage of the combinatorics in the index matrix to generalize to images from a different distribution than the one trained on. We have trained a VQ-VAE on MNIST digits 0 to 4 and then tested it on digits 5 to 9 as well as on the Fashion MNIST dataset. Figure 6 shows that the VQ-VAE generalizes almost perfectly from the low digits to the high ones, and it also generalizes to the quite different fashion images of clothes to some degree. A VAE, for instance, would not be able to that. Furthermore, Figure 7 shows that also the positive effect of the VQ-VAE for robustness to noise illustrated in Figure 5 generalizes to the Fashion MNIST data base.

**Modeling an episodic memory task**

An important goal of our modeling effort is to reproduce experimental results from episodic memory research and eventually make suggestions and predictions for new experiments. Here we relate to a recent experiment by Zöllner et al [47]. The experiment takes place in three days. At day one, participants are asked to move around an apartment in a virtual environment. The apartment has three main rooms: bedroom, kitchen, and bathroom. Half of the objects in the apartment are placed in a room where one would expect such an object, like a microwave in the kitchen, this is referred to as *congruent context*. Half of them are placed in a different room, like a toaster in a bathroom, referred to as *incongruent context*. Participants should first familiarize themselves with the apartment and are then instructed to do some tasks and interact with some of both congruent and incongruent objects, for example to make a sandwich with the toaster. This provides some control over the level of attention with which the different objects are perceived.
Fig 6. Generalization of the VQ-VAE to other data sets. A VQ-VAE network trained on half of the MNIST dataset digits (digits 0 to 4) is applied to three types of samples: MNIST images of digits 0 to 4 (in sample), MNIST images of digits 5 to 9 (out of sample but share the same input distribution), and images from the Fashion MNIST dataset (out of sample and different than input distribution). The reconstructed images of these three types of inputs are then tested for recognition accuracy using an MNIST classifier for digits 0 to 9 and a Fashion MNIST classifier images of clothes.

Fig 7. Semantics learned by the VQ-VAE improves classification accuracy for out of distribution samples. The VQ-VAE has been trained on the MNIST data set, digits 0 to 9, and achieves an improvement in classification accuracy on noisy images also for the quite different stimuli of the Fashion MNIST data set.

Participants are then tested on the next day on two tasks. In the recognition task, participants rank how confident they are that they have seen a specific household object and, if they think they have seen it, decide which room it was in. In the spatial recall task, participants drag a household object into a map of the apartment and drop it at the specific location where they think they have seen it. Both tasks are repeated several times with different objects. The same tasks are performed after seven days to check how memory changes over time. Since the results show no significant difference between day two and day eight and we are not modeling memory accuracy over time we pool the data from both days.

To reproduce this experiment with our model we pad the images to size $32 \times 32$ and augment them by three different backgrounds in the bottom half: A background with triangles for digits 0 to 3, squares for digits 4 to 6, and circles for digits 7 to 9. The backgrounds provide a context for the digits that can be congruent, e.g. a 3 in front of
The algorithm is trained on the congruent data and learns the relationship between digits and the background in an unsupervised manner. Then it is tested on both the congruent and incongruent data.

triangles, or incongruent, e.g. a 5 in front of circles, see Figure 8. We use only the bottom half, so that it is possible to show the model only the object without background, i.e. only the upper half. With a more flexible attention mechanism we could also use backgrounds across the whole image. The model implicitly learns the association between a digit and its congruent context by repeated exposure, e.g. 2 is always in the room with triangles. The model is trained only on congruent data and then tested on congruent as well as incongruent data. The different levels of attention are modeled by selecting various fractions of index matrix, the latent representation.

The model simulation then goes as follows: First the VQ-VAE and the PixelCNN are trained on the congruent data set. Then a number of congruent and incongruent images are shown to the system and stored in memory traces with varying levels of attention, i.e. with 5% (low attention), 52% (medium attention), or 63% (high attention) of the index matrix stored. The stored memory traces are then recalled by the network with semantic completion by the PixelCNN. A trained classifier for digits and another one for backgrounds are used to model the responses of the humans. If the digit classifier recognizes the digit from the recalled image correctly, this counts as if the subject remembers having seen the object. Only then is the background classifier applied to determine the type of background.

Since the PixelCNN has been trained only on congruent examples, it has a tendency to fill in the congruent background in the bottom half of the image if it has stored a particular number at attention level 52%, i.e. only the top half. However, if attention level is higher, say 63%, the PixelCNN might infer an incongruent background from the bits that are preserved about it in the memory trace and complete it. That means, for low attention levels, one would expect that the model always recalls the congruent background, while for high attention levels, it either recalls the episodically correct background or, if it fails to do so, it recalls the congruent background. Thus, the results should be trivial for congruent images, because always the congruent background is recalled, but interesting for incongruent images, because, depending on the attention level, the model either correctly recalls the incongruent background or plausibly recalls the congruent background. It should usually not recall an incorrect and incongruent background.

Experimental as well as simulation result are shown in Figure 9 in a direct comparison. The left panel shows the fraction of correctly recalled contexts for congruent and incongruent cases depending on the attention level. In both, experiments and model simulations, we see the trivial behavior of high correct recall for the congruent cases and a strong dependence on attention level for the incongruent cases. But congruent cases are always recalled better than incongruent ones, even for high attention levels. The right panel shows more detailed result for the incongruent cases. The blue sections indicate the correct recalls, called episodic because they need to be explicitly remembered; the orange sections indicate the incorrect but congruent recalls, called semantic because they can be semantically inferred from the object or digit; the gray sections indicate the completely wrong recall, neither correct not congruent. The simulation results match the experimental results quite well. To obtain a good fit, we tuned the three attention levels in the model, which are not well constrained by the experimentally determined attention levels in the subjects. However, the appearance of wrong recalls and their ratio to the semantic and episodic recalls emerge from the model.

The results in the experiments as well as the model simulations can be summarizes as follows:

- Congruent contexts are recalled better than incongruent ones, as there is no conflict between episodic memory and semantic information.
Fig 9. The effect of context and attention in the model and experiment. In the experiment, subjects explored an apartment in a virtual reality environment. Half of the household objects in the apartment were placed in an incongruent room. Later they were asked how sure they are if they have seen the incongruent objects and in which room they saw it. It is assumed that the objects that were reported to be seen with higher confidence had been seen with higher attention during the task. Episodic means remembered correctly, semantic means remembered in the semantically congruent room even though it was in an incongruent room and wrong means remembered in an incongruent third room. The model matches the trend in the experimental data. Objects are remembered better in congruent context and attention improves the memory accuracy. Also in the incongruent case the items that were not remembered correctly, were more often remembered semantically than wrong.

- Interaction with objects (i.e. paying attention) increases memory accuracy in both congruent and incongruent cases.
- Contexts that are not remembered episodically correctly are more often remembered semantically congruently than completely wrong.

Conclusion

Here, we present a model of generative episodic memory on a rather abstract level with a network architecture combining known methods from machine learning, namely VQ-VAE and PixelCNN. It can process real images, includes the potential for spatial attentional selection (although still in a very primitive form), can represent images quite different from those trained on, and models extraction of semantic information by compression, which relates to abstraction, and quantization, which relates to categorization. The two models most closely related to ours [23, 25] are based on a VQA, which lacks some of the advantages of a VQ-VAE and can therefore neither represent quite different images nor model spatial attentional selection in any way, nor does it include categorization of input features.

It is debatable whether machine learning methods are a good language to model the brain like we do here. However, convolutional neural networks as well as recurrent neural networks, on which our model is based, were inspired by the brain and are remarkably successful also in computational neuroscience [35, 36, 37, 51, 52]. Furthermore, they offer the advantage of efficiency, so that real world images can be processed. This is an important factor, since the frequently used artificial random stimuli in earlier modeling studies lack the statistical structure and regularities that are essential in studying the interaction between episodic memory and semantic information. Without statistical regularities that can be exploited, episodic memory can by design not be generative.

Our model shows that and how generative episodic memory can work in principle. It supports our conceptual framework for human episodic memory: (i) Sensory input (an image in our case) is processed by a multi-layer perceptual-semantic network, e.g. the visual system, to generate a hierarchical more abstract representation. (ii) Some aspects of this representation, the episodic gist, are selected, presumably by attention and depending on many factors. (iii) The selected parts are then stored in form of a memory trace in hippocampus. The trace contains pointers to the selected semantic elements in the hierarchical representation. (iv) During recall, a memory trace is reactivated in hippocampus. (v) The pointers in the memory trace in turn reactivate the semantic elements. (vi) Semantic information is finally used to fill in missing parts in a dynamic process. The latter step makes episodic memory generative, and we call the recall process scenario construction.

In our model, Step (i) is realized by the encoder of the VQ-VAE plus the quantization of the feature vectors, Step (ii) by selecting some fraction of the index matrix, Step (iii) by storing the partial index matrix, Steps (iv) and (v) by retrieving the partial index matrix, and Step (vi) by the PixelCNN and the decoder of the VQ-VAE.
The model shows good semantic completion capabilities. It is remarkable how well the PixelCNN generates plausible complete images even from small fragments, where faithful reconstructions are not possible, see Figure 4. The system is even able to generate plausible images from nothing (not shown).

Two factors in the model contribute to its capacity efficiency, compression and decompression in the VQ-VAE as well as the semantic completion in the PixelCNN. We have estimated that compression contributes a factor of about 30 while one can infer from Figure 4 that the semantic completion only contributes a factor of up to 2 to the overall compression of input images into the memory traces. This is in line with our hypothesis that semantic completion does not primarily contribute to the capacity efficiency but serves other purposes. Firstly, it is plausible to assume that encoding and storage of an episode is limited by the attentional bottleneck during the experience of the episode. Semantic completion can help to fill in those missing parts that we were just not able to attend to in the episodic situation. Secondly, semantic completion can help to generalize better. It has been hypothesized that the main purpose of episodic memory is not to remember the past but to help us make decisions for the future [53, 54, 55]. Thus, if our knowledge about the world changes, maybe also our memories of the past should change to be maximally useful to deal with the future. Semantic completion can do exactly that.

We have successfully modeled the episodic memory experiment by Zöllner et al. [47]. Both, experiments and simulations, show that congruent contexts are recalled better than incongruent ones and that incorrectly recalled contexts in incongruent cases are more often remembered semantically correct than completely wrong. By designing the stimuli appropriately and tuning the selection percentages for the index matrix for the three attention levels we were able to achieve a very good fit to the experimental data. Due to the available degrees of freedom to match the experimental results, our model does not yet have strong explanatory power. However, it is not obvious and not a result of tuning that wrong recalls emerge in the incongruent cases and that the ratio to the semantically correct recalls match so well. These are emergent properties of the model.

Overall, we feel this model advances our understanding and sharpens our concepts of generative episodic memory. However, there are many ways in which the model can and should be developed further. (i) The attentional selection is rather limited. As one of the next steps we plan to make it more flexible. (ii) Even though the encoder is hierarchical, consistent with our conceptual framework, the index matrix, on which the selection and semantic completion are done, is not. We plan to adopt a hierarchical version of the VQ-VAE [56] to be able to apply semantic completion to a truly hierarchical representation. (iii) The storage process in the hippocampus is not modeled at all. We plan to address this by adding a model for one-shot storage of pattern sequences in hippocamal memory [57]. This would also allow us to investigate storage of sequential episodes, not just snapshots. Sequentiality has been claimed to be one essential characteristics of episodic memory [16, 58]. (iv) Besides developing the model further, we will also continue to focus on modeling experiments on human episodic memory to constrain the model better and contribute to the design of new experiments.

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Methods

Vector-Quantized Variational AutoEncoders (VQ-VAE) are autoencoders with a discrete latent representation that process input in three steps. (i) The encoder, which is a Convolutional Neural Network (CNN), compresses the input $x$ to generate the encoding $z_e$, which is an array of $w \times h \times d$-dimensional feature vectors. (ii) These feature vectors are then quantized with the help of $k$ codebook vectors $e_l \in \mathbb{R}^d$ according to the Vector Quantization (VQ) framework in equation (1), i.e. each one is mapped to the closest codebook vector $e_l$, and index matrix $z_x$ contains the corresponding indices.

$$z_x^{(i,j)} = \arg\min_l \| z_e^{(i,j)} - e_l \|_2$$

$$z_q^{(i,j)} = e_{z_x^{(i,j)}}$$

with $i \in \{1, \ldots, w\}$, $j \in \{1, \ldots, h\}$, $l \in \{1, \ldots, k\}$
The codebook vectors are initialized randomly, but they get optimized during training together with the encoder and decoder. The quantized version of \( z_e \) is denoted \( z_q \) and is a \( w \times h \) array of codebook vectors. (iii) The decoder, which is a deconvolutional neural network, then generates a reconstruction \( y \) of the input \( x \) based on the given \( z_q \).

A VQ-VAE can be trained end to end based on the loss function

\[
L = \log p(y = x \mid z_q(x)) + \| \text{sg}(z_e(x)) - e \|^2_2 + \beta \| z_e(x) - \text{sg}(e) \|^2_2
\]

The first term is the reconstruction loss, which is the negative log-likelihood of the decoder output \( y \) being equal to the input \( x \), given the quantized latent representation \( z_q \); this term optimizes the decoder and the encoder. The second term is the VQ objective, which optimizes the codebook vectors. This term uses the \( l_2 \) norm to push the codebook vectors towards \( z_e \) and minimize the quantization error. Since the codebook vectors \( e \) may not train as fast as the encoder, it might happen that the encoder outputs grow arbitrarily large. To make sure that the encoder commits to the codebook vector the third term is added. Essentially it pushes the encoder outputs toward the codebook vectors. This third term is called the commitment loss and constrains the size of the encoder outputs [26].

Since the quantization is a discrete operation, it is not possible to calculate its gradient for back propagation. Therefore, the stop gradient (sg) operator is introduced here. During the forward pass it works like an identity operator. During the backward pass (backpropagation), the gradient \( \nabla z L \) is passed directly from \( z_q \) to \( z_e \). The second and the third term have identical values, the second one updates the codebook \( e \) via quantization (i.e. due to non-zero \( \nabla z L \)), while the third one only affects the encoder.

A VQ-VAE by itself is not a generative model. However, it’s quantized index matrix \( (z_q) \) makes it possible to sample new data with the help of a PixelCNN [34]. A PixelCNN is a well known autoregressive model, which is mainly used to generate new images given the training data distribution. The basic principle of this model is that each pixel in an image has a probability distribution that depends on all the pixels that came before it:

\[
p(x) = \prod_{i=1}^{D} p(x_i \mid x_{<i}) \text{ where } x_{<i} = [x_1, \ldots, x_{i-1}]
\]

PixelCNNs generate images pixel by pixel and in a sequence (from top left to bottom right) conditioned on all previously sampled pixels. This process is slow for large images, however in our case we use the PixelCNN only on the index matrix \( z_e \), which is much smaller. After training, the model can either complete a partial index matrix or even generate a new one from scratch based on the semantic information learned from the training data. This is then converted to an array \( z_q \) of codebook vectors and passed to the decoder to generate the output.

In this work we use a gated PixelCNN [34] with the activation function

\[
y = \tanh(W_{k,f} * x) \odot \sigma(W_{k,g} * x)
\]

instead of the more common rectified linear activation function. \( \sigma \) is the sigmoid function, \( k \) is the number of the layer, \( \odot \) is the element-wise product and \( * \) represents the convolution operator. These multiplicative units help the network to model more complex functions [34].

The digit classifier network used in this paper is a basic CNN with three convolutional layers, which was trained on digits in both congruent and incongruent context. This network has an accuracy of 99.1% on test data. The context classifier is a simple pattern matching algorithm that assigns the pattern class based on mean square error.

References

1. Clayton NS, Salwiczek LH, Dickinson A. Episodic memory. Current Biology. 2007;17(6):189-91.
2. Reisberg D. The Oxford handbook of cognitive psychology. Oxford University Press; 2013.
3. Tulving E. Organization of memory. Episodic and semantic memory. 1972.
4. Bartlett FC, Bartlett FC. Remembering: A study in experimental and social psychology. Cambridge University Press; 1995.
5. Sachs JS. Recognition memory for syntactic and semantic aspects of connected discourse. Perception & Psychophysics. 1967;2(9):437-42.
6. Deese J. On the prediction of occurrence of particular verbal intrusions in immediate recall. Journal of experimental psychology. 1959;58(1):17.
7. Roediger HL, McDermott KB. Creating false memories: Remembering words not presented in lists. Journal of experimental psychology: Learning, Memory, and Cognition. 1995;21(4):803.
8. Greenberg DL, Verfaellie M. Interdependence of episodic and semantic memory: Evidence from neuropsychology. Journal of the International Neuropsychological society. 2010;16(5):748-53.

9. Devitt AL, Addis DR, Schacter DL. Episodic and semantic content of memory and imagination: A multilevel analysis. Memory & Cognition. 2017;45(7):1078-94.

10. Hirst W, Echterhoff G. Remembering in conversations: The social sharing and reshaping of memories. Annual review of psychology. 2012;63:55-79.

11. Deuker L, Müller AR, Montag C, Markett S, Reuter M, Fell J, et al. Playing nice: a multi-methodological study on the effects of social conformity on memory. Frontiers in Human Neuroscience. 2013;7:79.

12. Axmacher N, Do Lam AT, Kessler H, Fell J. Natural memory beyond the storage model: repression, trauma, and the construction of a personal past. Frontiers in human neuroscience. 2010;4:211.

13. Herten N, Otto T, Wolf OT. The role of eye fixation in memory enhancement under stress—An eye tracking study. Neurobiology of learning and memory. 2017;140:134-44.

14. Schacter DL, Addis DR. Memory and Imagination: Perspectives on Constructive Episodic Simulation. The Cambridge Handbook of the Imagination. 2020.

15. Addis DR. Mental time travel? A neurocognitive model of event simulation. Review of Philosophy and Psychology. 2020;11(2):233-59.

16. Cheng S, Werning M. What is episodic memory if it is a natural kind? Synthese. 2016;193(5):1345-85.

17. Cheng S, Frank LM. The structure of networks that produce the transformation from grid cells to place cells. Neuroscience. 2011;197:293-306.

18. Neher T, Cheng S, Wiskott L. Memory storage fidelity in the hippocampal circuit: the role of subregions and input statistics. PLoS computational biology. 2015;11(5):e1004250.

19. Rolls ET. A model of the operation of the hippocampus and entorhinal cortex in memory. International Journal of Neural Systems. 1995;6:51-70.

20. Jensen O, Lisman JE. Novel lists of 7 ± 2 known items can be reliably stored in an oscillatory short-term memory network: interaction with long-term memory. Learning & Memory. 1996;3(2-3):257-63.

21. Becker S. A computational principle for hippocampal learning and neurogenesis. Hippocampus. 2005;15(6):722-38.

22. Cheng S, Werning M, Suddendorf T. Dissociating memory traces and scenario construction in mental time travel. Neuroscience & Biobehavioral Reviews. 2016;60:82-9.

23. Bates CJ, Jacobs RA. Efficient data compression in perception and perceptual memory. Psychological review. 2020;127(5):891.

24. Nagy DG, Török B, Orbán G. Optimal forgetting: Semantic compression of episodic memories. PLoS Computational Biology. 2020;16(10):e1008367.

25. Kingma DP, Welling M. Auto-encoding variational bayes. arXiv preprint arXiv:13126114. 2013.

26. Oord Avd, Vinyals O, Kavukcuoglu K. Neural discrete representation learning. arXiv preprint arXiv:171100937. 2017.

27. Schacter DL, Guerin SA, Jacques PL. Memory distortion: an adaptive perspective. Trends in Cognitive Sciences. 2011;15(10):467-74.

28. Koutstaal W, Schacter DL. Gist-based false recognition of pictures in older and younger adults. Journal of memory and language. 1997;37(4):555-83.

29. Oliva A. Gist of the scene. In: Neurobiology of attention. Elsevier; 2005. p. 251-6.

30. Graham KS, Simons JS, Pratt KH, Patterson K, Hodges JR. Insights from semantic dementia on the relationship between episodic and semantic memory. Neuropsychologia. 2000;38(3):313-24.

31. Fang J, Rüther N, Bellebaum C, Wiskott L, Cheng S. The interaction between semantic representation and episodic memory. Neural Computation. 2018;30(2):293-332.

32. Collins AM, Quillian MR. Retrieval time from semantic memory. Journal of verbal learning and verbal behavior. 1969;8(2):240-7.

33. Irish M, Piguet O. The pivotal role of semantic memory in remembering the past and imagining the future. Frontiers in behavioral neuroscience. 2013;7:27.
34. Oord Avd, Kalchbrenner N, Vinyals O, Espeholt L, Graves A, Kavukcuoglu K. Conditional image generation with pixelcnn decoders. arXiv preprint arXiv:160605328. 2016.
35. Kuzovkin I, Vicente R, Petton M, Lachaux JP, Baciu M, Kahane P, et al. Activations of deep convolutional neural networks are aligned with gamma band activity of human visual cortex. Communications biology. 2018;1(1):1-12.
36. Lindsay GW. Convolutional neural networks as a model of the visual system: Past, present, and future. Journal of cognitive neuroscience. 2021;33(10):2017-31.
37. Yamins DL, Hong H, Cadieu CF, Solomon EA, Seibert D, DiCarlo JJ. Performance-optimized hierarchical models predict neural responses in higher visual cortex. Proceedings of the national academy of sciences. 2014;111(23):8619-24.
38. Xia R, Guan S, Sheinberg DL. A multilayered story of memory retrieval. Neuron. 2015;86(3):610-2.
39. Takeda M. Brain mechanisms of visual long-term memory retrieval in primates. Neuroscience research. 2019;142:7-15.
40. Al-Tahan H, Mohsenzadeh Y. Reconstructing feedback representations in the ventral visual pathway with a generative adversarial autoencoder. PLoS Computational Biology. 2021;17(3):e1008775.
41. Hu R, Jacobs RA. Semantic influence on visual working memory of object identity and location. Cognition. 2021;217.
42. Michaelian K. Generative Memory. Philosophical Psychology. 2011;24(3):323-42.
43. Tang H, Schrimpf M, Lotter W, Moerman C, Paredes A, Caro JO, et al. Recurrent computations for visual pattern completion. Proceedings of the National Academy of Sciences. 2018;115(35):8835-40.
44. Carrillo-Reid L, Yuste R. Playing the piano with the cortex: role of neuronal ensembles and pattern completion in perception and behavior. Current opinion in neurobiology. 2020;64:89-95.
45. Schacter DL, Addis DR. The ghosts of past and future. Nature. 2007;445(7123):27-7.
46. LeCun Y. The MNIST database of handwritten digits; 1998. Available from: http://yann.lecun.com/exdb/mnist/.
47. Zöllner C, Klein N, Cheng S, Schubotz R, Axmacher N, Wolf OT. Where was the Toaster? Interplay of Episodic Memory Traces and Semantic Knowledge during Scenario Construction. PsyArXiv; 2021. Available from: https://psyarxiv.com/2kmwy.
48. Walker J, Razavi A, Oord Avd. Predicting Video with VQVAE. arXiv preprint arXiv:210301950. 2021.
49. Mathieu M, Couprie C, LeCun Y. Deep multi-scale video prediction beyond mean square error. arXiv preprint arXiv:151105440. 2015.
50. Bhowick D, Gupta DK, Maiti S, Shankar U. Stacked autoencoders based machine learning for noise reduction and signal reconstruction in geophysical data. arXiv: Computational Engineering, Finance, and Science. 2019.
51. Savage N. How AI and neuroscience drive each other forwards. Nature. 2019;571(7766):S15-5.
52. Papadimitriou CH, Vempala SS, Mitropolsky D, Collins M, Maass W. Brain computation by assemblies of neurons. Proceedings of the National Academy of Sciences. 2020;117(25):14464-72.
53. Schacter DL, Addis DR. The cognitive neuroscience of constructive memory: remembering the past and imagining the future. Philosophical Transactions of the Royal Society B: Biological Sciences. 2007;362(1481):773-86.
54. Schacter DL, Addis DR. The ghosts of past and future. Nature. 2007;445(7123):27-7.
55. La Corte V, Piolino P. On the Role of Personal semantic memory and temporal distance in episodic future thinking: the TEDIFT model. Frontiers in human neuroscience. 2016;10:385.
56. Razavi A, van den Oord A, Vinyals O. Generating Diverse High-Fidelity Images with VQ-VAE-2; 2019.
57. Melchior J, Bayati M, Azizi A, Cheng S, Wiskott L. A Hippocampus Model for Online One-Shot Storage of Pattern Sequences; 2019. e-print arXiv:1905.12937. Available from: https://arxiv.org/abs/1905.12937.
58. Cheng S. The CRISP theory of hippocampal function in episodic memory. Frontiers in neural circuits. 2013;7:88.