**Summary**

By making a dynamical systems hypothesis, LFADS reduces the observed spiking to a set of low dimensional latent factors. The primary goal of LFADS is to infer smooth dynamics from recorded spike trains on a single trial basis.

Additional benefits:

* A low dimensional set of temporal factors to explain the observed spike trains.
* An RNN to produce the smooth data
* A set of initial conditions that can be used as code for the trials.
* LFADS infers inputs

The idea of inferring inputs is that if a powerful dynamical non linear system is unable to explain the data, then there must be some external perturbation.

LFADS Model

The LFADS is an extension to VAE, which comprises of two components a generator and an encoder. The generator assumes that the data x depends on stochastic latent variables z, samples of which are drawn from ). The datapoints are then drawn from the conditional distribution .

The encoder of VAE transforms the data x into a conditional distribution over x given by , which is an approximation to = . can be thought of as an encoder from data x to data specific latent code z, and decoder as the opposite. On a whole from data x we construct , from which we sample The used to construct P(x|z) from which we sample . Ideally, we want to be equal to our data x.

The loss function also involves KL divergence between and . Since z depends on and , we calculate the KL between and P( and and P().

LFADS Generator

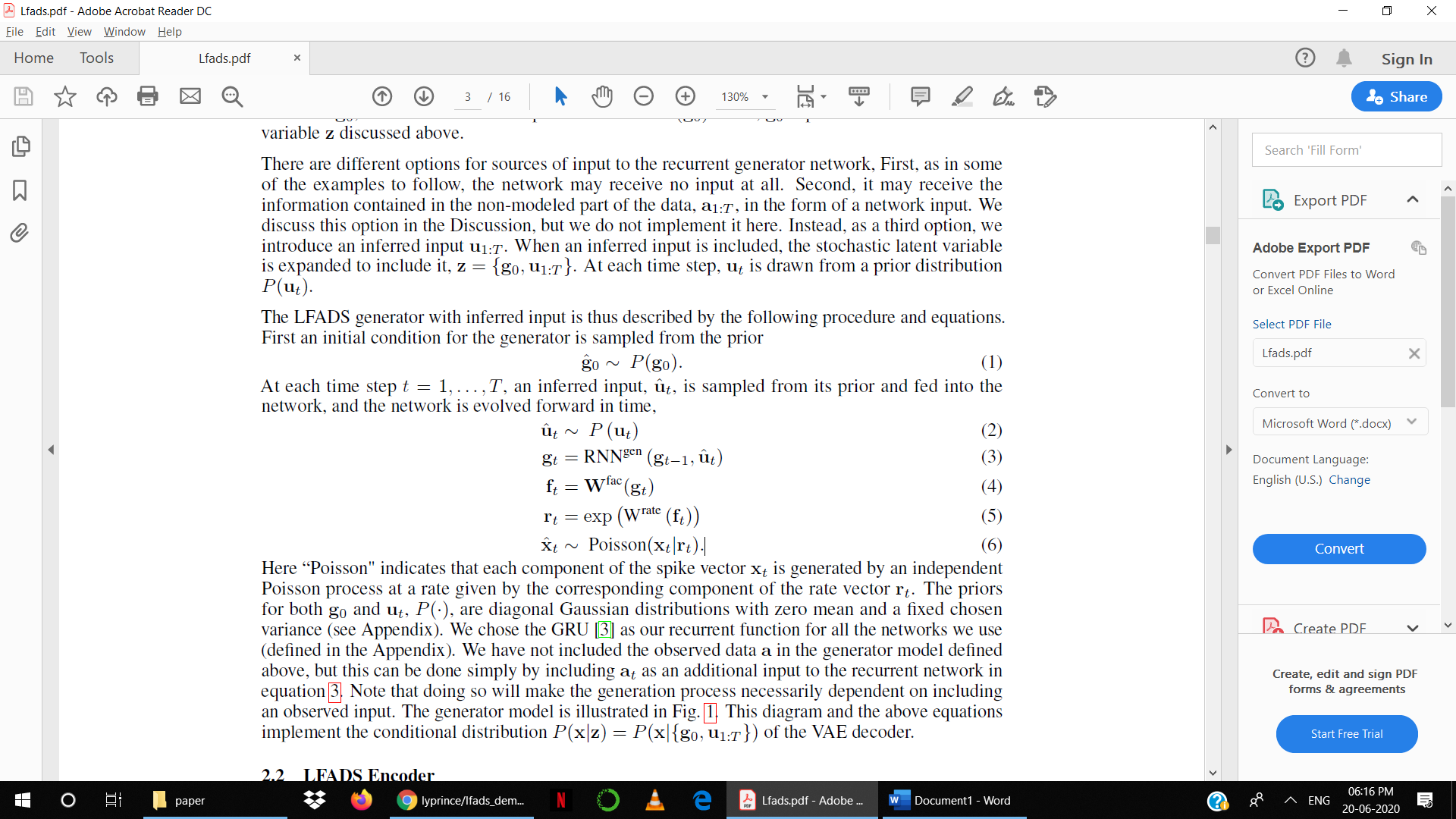
The represents spike trains recorded from D neurons. Each instance represents a trial. represents the stimuli being presented or other experimental features. We must distinguish between the time series x and a. The conditional distribution P(x|z) depends only on x, whereas the posterior Q(z|x,a) depends both on x and a.

LFADS assumes that the data is generated from a Poisson process with underlying rates . The aim of LFADS is to infer a lower dimensional set from which the rates can be re constructed.

The factors are dependent on state vector of RNN. The initial condition is drawn from a prior distribution P(. is part of the stochastic latent variable.

We give the inferred input as input to our RNN. The stochastic latent variable now includes, , where is drawn from prior P().

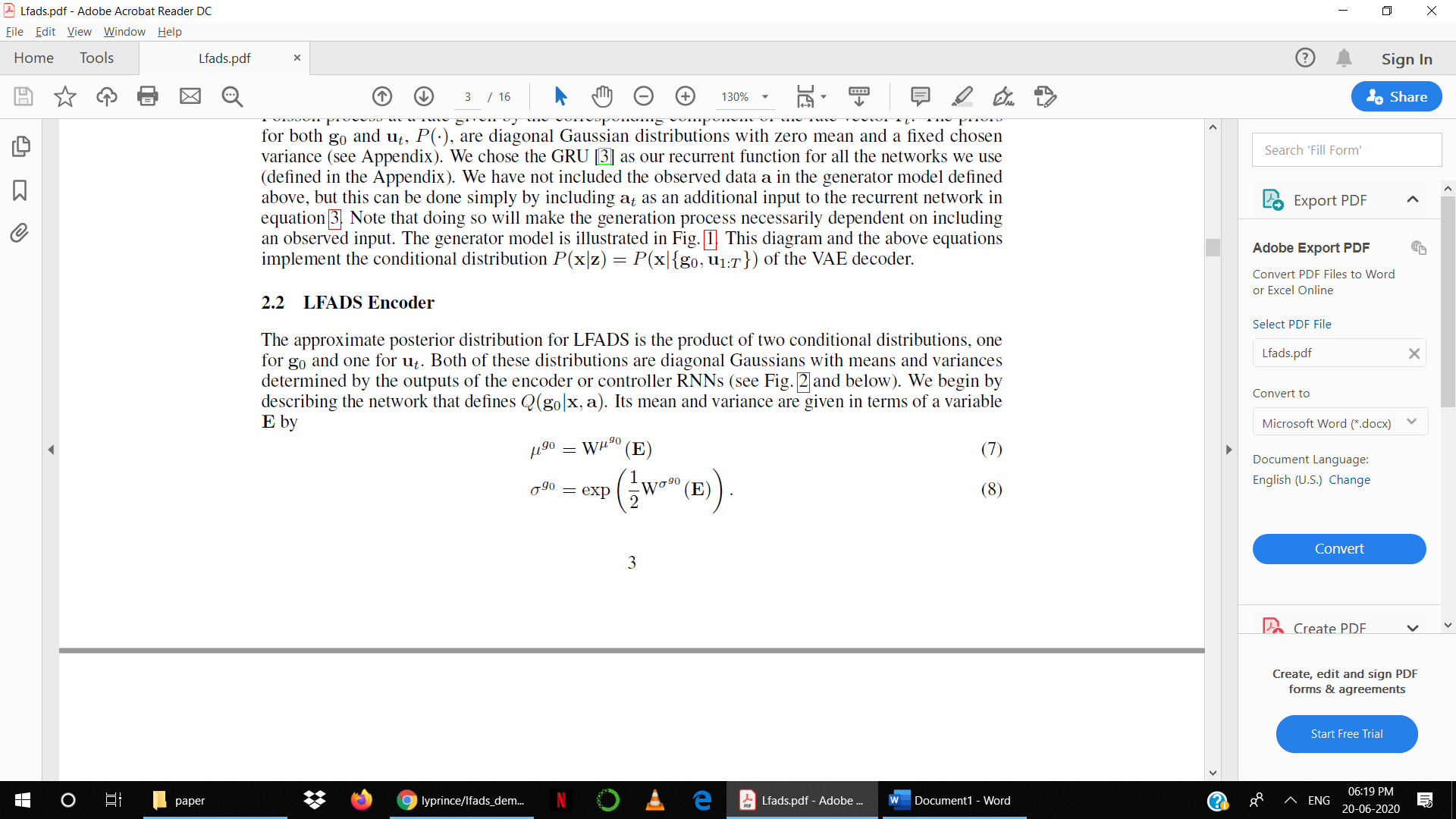
The LFADS equations are, with sampled from P().

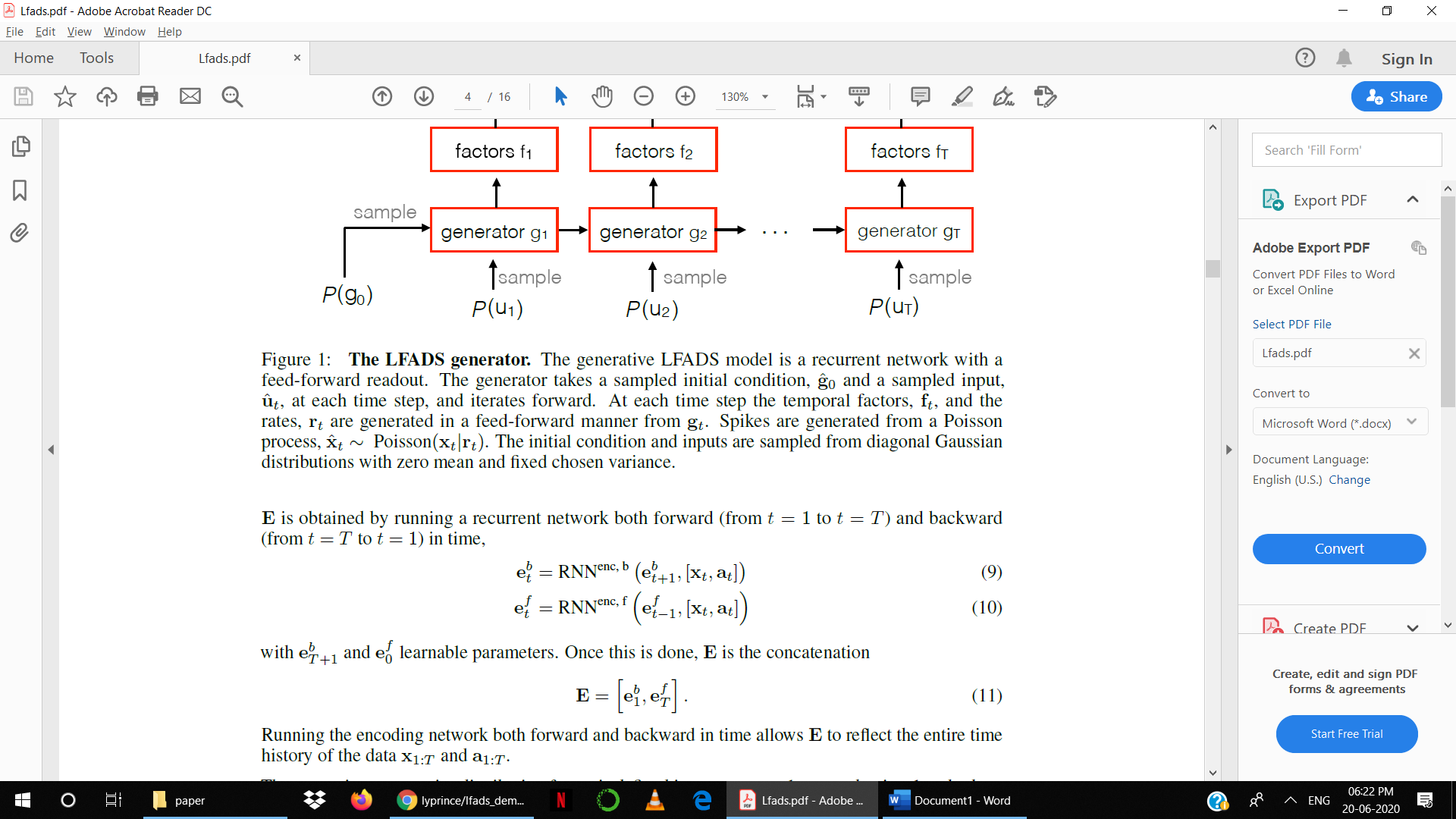


GRU is chosen as the recurrent function in the implementation. The above LFADS represents

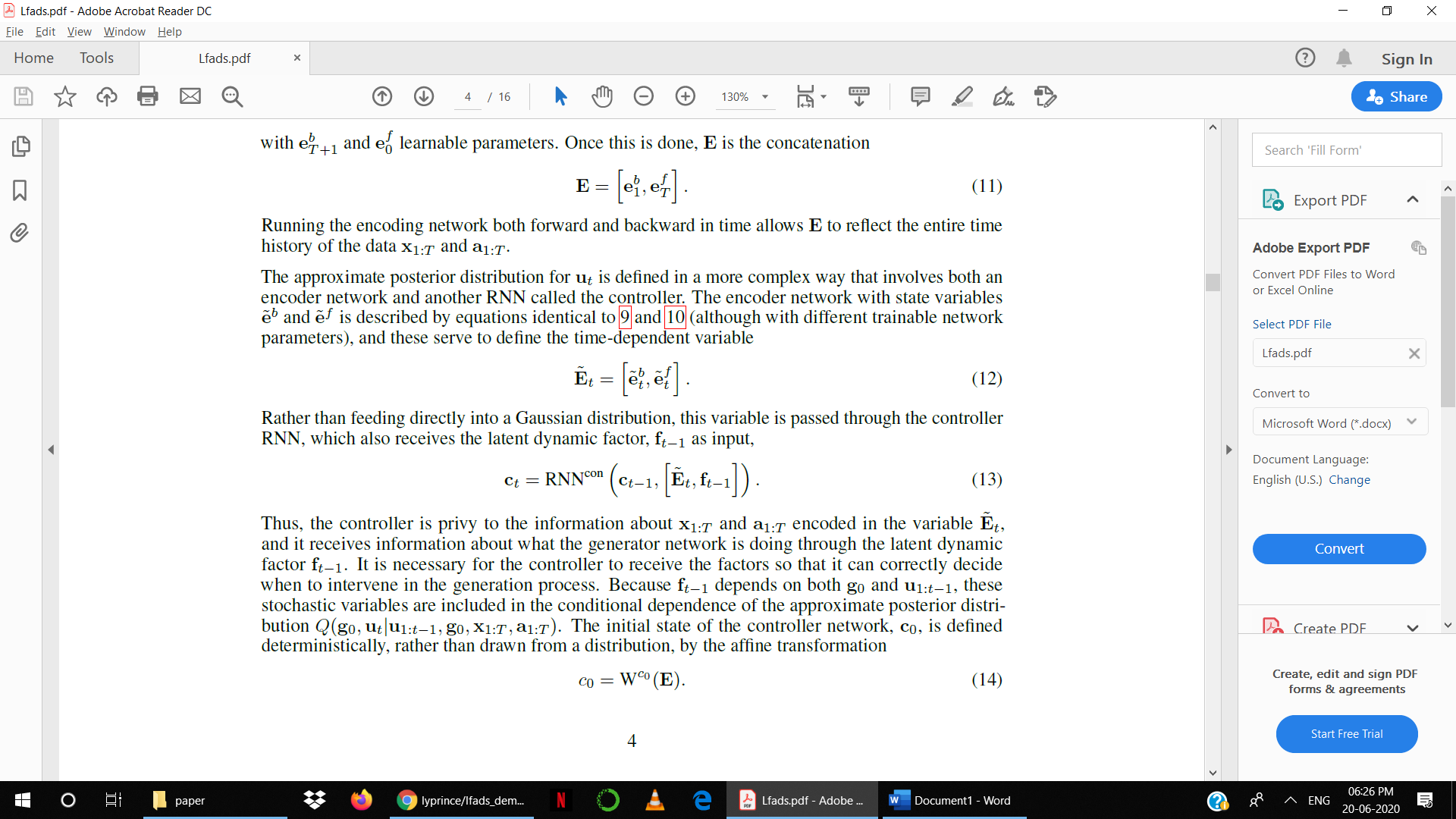
LFADS Encoder

Thus, the approximate posterior for generator is product of conditional distributions one for and one for . The mean and variance of are given by:

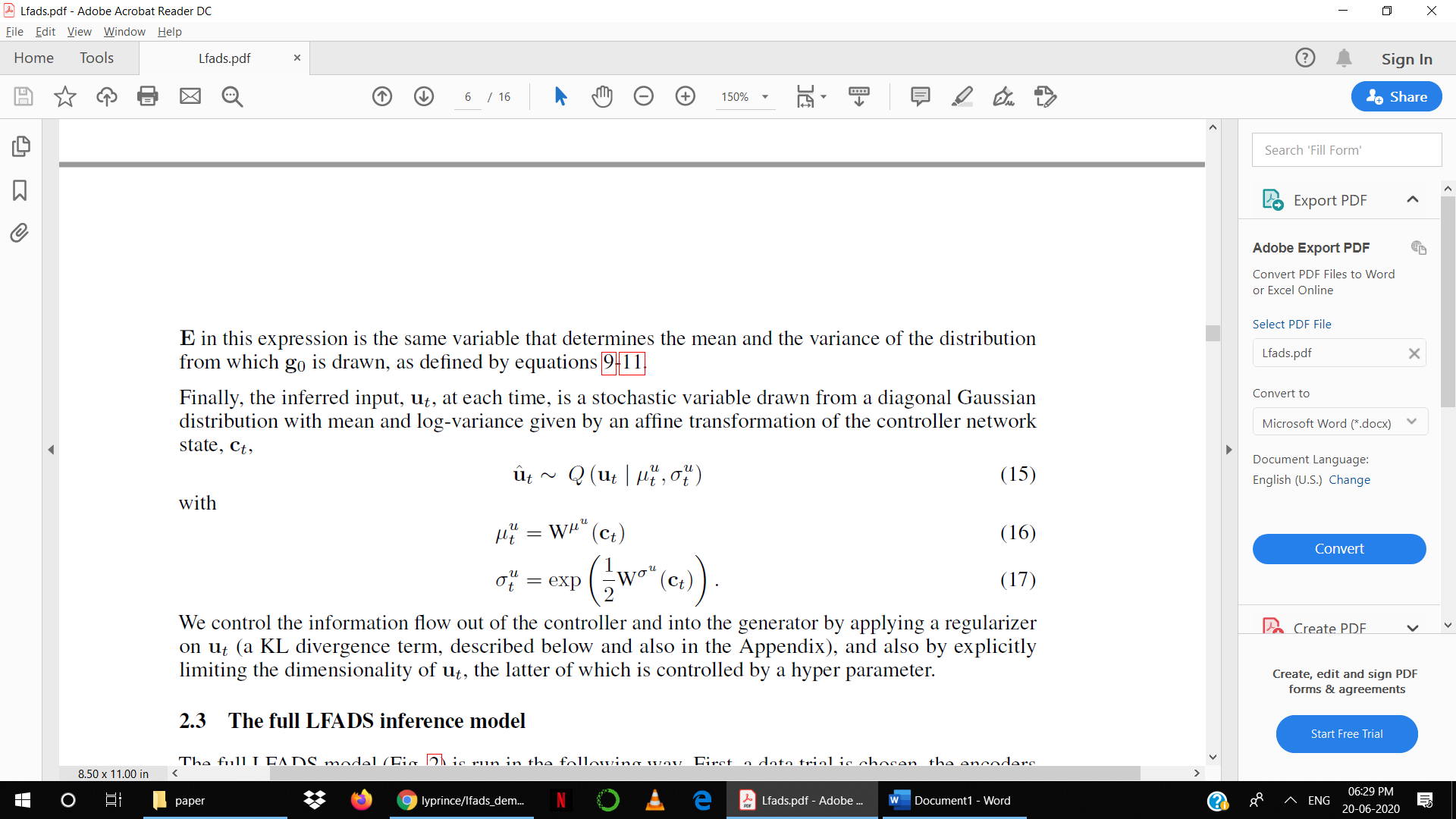


E is obtained by running both forward and backward in time and concatenation of 

Running the encoder both forward and back allows E to represent entire data.

The approximate posterior for involves another RNN called controller. The state of controller is given bywhere E(tilde) is similar to E(.

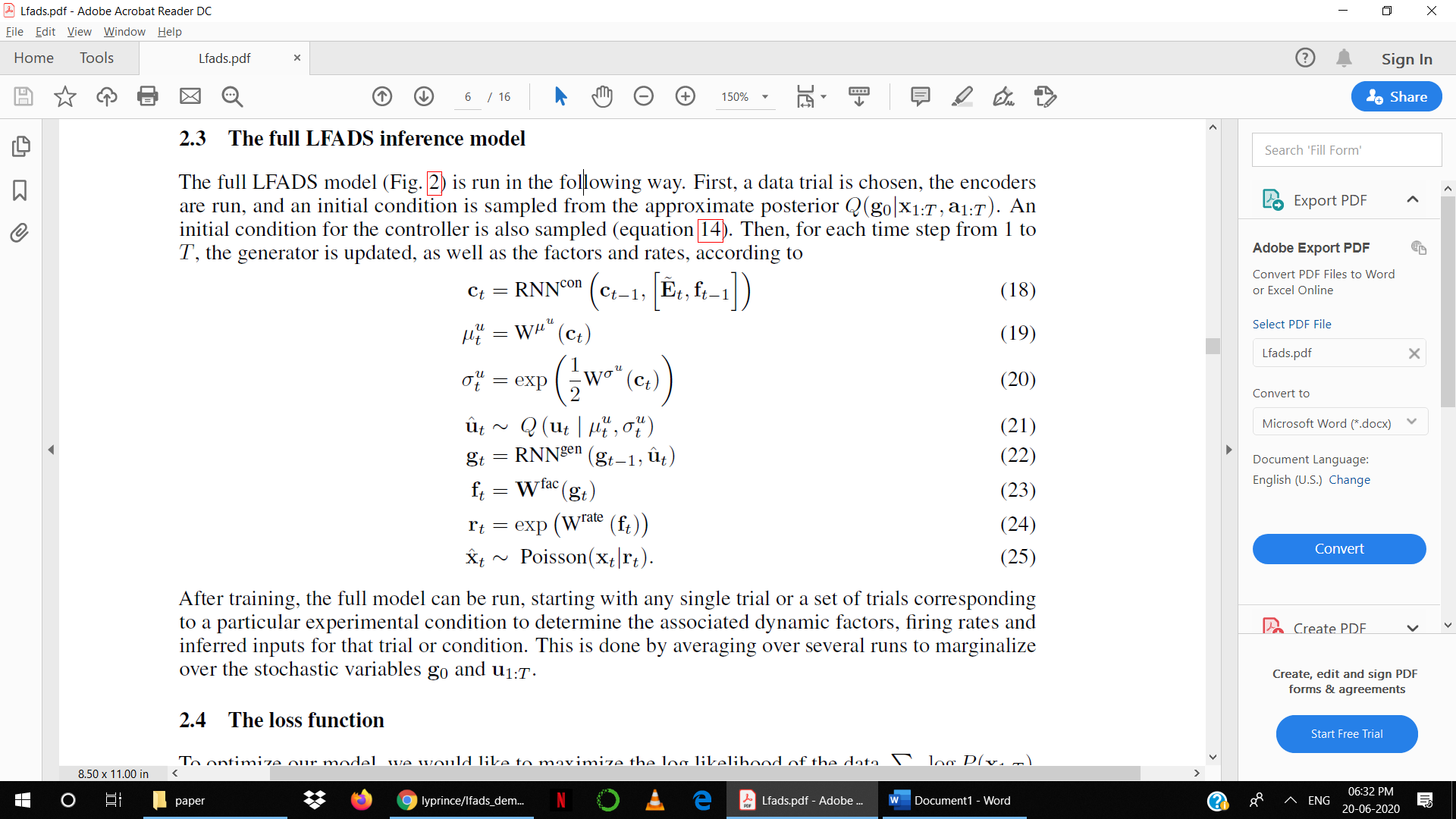
The controller also receives the information about the generator through and can intervene accordingly. The is given by affine transformation of E. The equations for are given by



We control the information flow from controller into generator with help of KL on .

Full LFADS model

First a data trial is selected. The encoders are run to calculate E. and are calculated from E. Then for time steps t = 1:T



The total loss for LFADS framework is given by reconstruction loss plus the KL divergence loss from g0 and ut.