

## tf.contrib.distributions.bijectors.CholeskyOuterProduct


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Class **CholeskyOuterProduct**Inherits From: [Bijector](#)Defined in [tensorflow/contrib/distributions/python/ops/bijectors/cholesky\\_outer\\_product\\_impl.py](#).See the guide: [Random variable transformations \(contrib\) > Bijectors](#)Compute  $g(X) = X @ X.T$ ;  $X$  is lower-triangular, positive-diagonal matrix.`event_ndims` must be 0 or 2, i.e., scalar or matrix. **Note:** the upper-triangular part of  $X$  is ignored (whether or not its zero).

The surjectivity of  $g$  as a map from the set of  $n \times n$  positive-diagonal lower-triangular matrices to the set of SPD matrices follows immediately from executing the Cholesky factorization algorithm on an SPD matrix  $A$  to produce a positive-diagonal lower-triangular matrix  $L$  such that  $A = L @ L.T$ .

To prove the injectivity of  $g$ , suppose that  $L_1$  and  $L_2$  are lower-triangular with positive diagonals and satisfy  $A = L_1 @ L_1.T = L_2 @ L_2.T$ . Then  $inv(L_1) @ A @ inv(L_1).T = [inv(L_1) @ L_2] @ [inv(L_1) @ L_2].T = I$ . Setting  $L_3 := inv(L_1) @ L_2$ , that  $L_3$  is a positive-diagonal lower-triangular matrix follows from  $inv(L_1)$  being positive-diagonal lower-triangular (which follows from the diagonal of a triangular matrix being its spectrum), and that the product of two positive-diagonal lower-triangular matrices is another positive-diagonal lower-triangular matrix.

A simple inductive argument (proceeding one column of  $L_3$  at a time) shows that, if  $I = L_3 @ L_3.T$ , with  $L_3$  being lower-triangular with positive-diagonal, then  $L_3 = I$ . Thus,  $L_1 = L_2$ , proving injectivity of  $g$ .

Examples:

```
bijector.CholeskyOuterProduct(event_ndims=2).forward(x=[[1., 0], [2, 1]])  
# Result: [[1., 2], [2, 5]], i.e., x @ x.T  
  
bijector.CholeskyOuterProduct(event_ndims=2).inverse(y=[[1., 2], [2, 5]])  
# Result: [[1., 0], [2, 1]], i.e., cholesky(y).
```

## Properties

**dtype**

dtype of `Tensor` s transformable by this distribution.

## `event_ndims`

Returns then number of event dimensions this bijector operates on.

## `graph_parents`

Returns this `Bijector` 's graph\_parents as a Python list.

## `is_constant_jacobian`

Returns true iff the Jacobian is not a function of x.

★ **Note:** Jacobian is either constant for both forward and inverse or neither.

Returns:

- `is_constant_jacobian`: Python `bool`.

## `name`

Returns the string name of this `Bijector`.

## `validate_args`

Returns True if Tensor arguments will be validated.

## Methods

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### `__init__`

```
__init__(
    event_ndims=2,
    validate_args=False,
    name='cholesky_outer_product'
)
```

Instantiates the `CholeskyOuterProduct` bijector.

Args:

- `event_ndims`: `constant int32` scalar `Tensor` indicating the number of dimensions associated with a particular draw from the distribution. Must be 0 or 2.
- `validate_args`: Python `bool` indicating whether arguments should be checked for correctness.
- `name`: Python `str` name given to ops managed by this object.

Raises:

- `ValueError`: if `event_ndims` is neither 0 or 2.

## forward

```
forward(  
    x,  
    name='forward'  
)
```

Returns the forward **Bijector** evaluation, i.e.,  $X = g(Y)$ .

Args:

- **x**: **Tensor** . The input to the "forward" evaluation.
- **name** : The name to give this op.

Returns:

**Tensor** .

Raises:

- **TypeError** : if **self.dtype** is specified and **x.dtype** is not **self.dtype** .
- **NotImplementedError** : if **\_forward** is not implemented.

## forward\_event\_shape

```
forward_event_shape(input_shape)
```

Shape of a single sample from a single batch as a **TensorShape** .

Same meaning as **forward\_event\_shape\_tensor** . May be only partially defined.

Args:

- **input\_shape** : **TensorShape** indicating event-portion shape passed into **forward** function.

Returns:

- **forward\_event\_shape\_tensor** : **TensorShape** indicating event-portion shape after applying **forward** . Possibly unknown.

## forward\_event\_shape\_tensor

```
forward_event_shape_tensor(  
    input_shape,  
    name='forward_event_shape_tensor'  
)
```

Shape of a single sample from a single batch as an **int32** 1D **Tensor** .

Args:

- **input\_shape** : **Tensor** , **int32** vector indicating event-portion shape passed into **forward** function.

- `name` : name to give to the op

Returns:

- `forward_event_shape_tensor` : `Tensor`, `int32` vector indicating event-portion shape after applying `forward`.

## forward\_log\_det\_jacobian

```
forward_log_det_jacobian(
    x,
    name='forward_log_det_jacobian'
)
```

Returns both the `forward_log_det_jacobian`.

Args:

- `x` : `Tensor`. The input to the "forward" Jacobian evaluation.
- `name` : The name to give this op.

Returns:

`Tensor`, if this bijector is injective. If not injective this is not implemented.

Raises:

- `TypeError` : if `self.dtype` is specified and `y.dtype` is not `self.dtype`.
- `NotImplementedError` : if neither `_forward_log_det_jacobian` nor `{_inverse, _inverse_log_det_jacobian}` are implemented, or this is a non-injective bijector.

## inverse

```
inverse(
    y,
    name='inverse'
)
```

Returns the inverse `Bijector` evaluation, i.e.,  $X = g^{-1}(Y)$ .

Args:

- `y` : `Tensor`. The input to the "inverse" evaluation.
- `name` : The name to give this op.

Returns:

`Tensor`, if this bijector is injective. If not injective, returns the k-tuple containing the unique `k` points `(x1, ..., xk)` such that  $g(x_i) = y$ .

Raises:

- `TypeError` : if `self.dtype` is specified and `y.dtype` is not `self.dtype` .
- `NotImplementedError` : if `_inverse` is not implemented.

## inverse\_event\_shape

```
inverse_event_shape(output_shape)
```

Shape of a single sample from a single batch as a `TensorShape` .

Same meaning as `inverse_event_shape_tensor` . May be only partially defined.

Args:

- `output_shape` : `TensorShape` indicating event-portion shape passed into `inverse` function.

Returns:

- `inverse_event_shape_tensor` : `TensorShape` indicating event-portion shape after applying `inverse` . Possibly unknown.

## inverse\_event\_shape\_tensor

```
inverse_event_shape_tensor(
    output_shape,
    name='inverse_event_shape_tensor'
)
```

Shape of a single sample from a single batch as an `int32` 1D `Tensor` .

Args:

- `output_shape` : `Tensor` , `int32` vector indicating event-portion shape passed into `inverse` function.
- `name` : name to give to the op

Returns:

- `inverse_event_shape_tensor` : `Tensor` , `int32` vector indicating event-portion shape after applying `inverse` .

## inverse\_log\_det\_jacobian

```
inverse_log_det_jacobian(
    y,
    name='inverse_log_det_jacobian'
)
```

Returns the  $(\log \circ \det \circ \text{Jacobian} \circ \text{inverse})(y)$ .

Mathematically, returns:  $\log(\det(dX/dY))(Y)$  . (Recall that:  $X = g^{-1}(Y)$  .)

Note that `forward_log_det_jacobian` is the negative of this function, evaluated at  $g^{-1}(y)$  .

Args:

- `y` : `Tensor` . The input to the "inverse" Jacobian evaluation.
- `name` : The name to give this op.

Returns:

`Tensor` , if this bijector is injective. If not injective, returns the tuple of local log det Jacobians, `log(det(Dg_i^{-1}(y)))` , where `g_i` is the restriction of `g` to the `i`th partition `Di` .

Raises:

- `TypeError` : if `self.dtype` is specified and `y.dtype` is not `self.dtype` .
- `NotImplementedError` : if `_inverse_log_det_jacobian` is not implemented.

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